Volatility spillovers and other market dynamics between cryptocurrencies and the equity market[‡]

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Abstract

Little is known about the market dynamics between the conventional equity market and cryptocurrencies, whilst such insights become increasingly important with the recent introduction of financial derivatives related to these coins. This study covers four well known phenomena in a bivariate setting, combining two stock indices (S&P500 and Nikkei 225) with five cryptocurrencies (Bitcoin, DASH, Litecoin, Monero, and Ripple), resulting in a number of new insights. Firstly, convincing evidence is found that the volatility of cryptocurrencies is highly affected by the dynamics of the equity market, whereas a vice versa effect is not present. Secondly, the findings provide no evidence for the presence of a traditional leverage effect in the returns of cryptocurrencies. Thirdly, the time varying correlation between the equity market and the cryptocurrencies approximates zero on average and is heavily affected by the volatility of both assets, whereas the correlation between Bitcoin and its peers is considerably higher and mainly event driven. Lastly, the past returns of both stock indices and the Bitcoin negatively impact the current returns of the (other) coins, while the effect in opposite direction is only marginal. However, this (cross) return predictability proved to increase substantially over longer horizons.

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Contents

1. Introduction

What a ride it has been. Over the past year, the value of the Bitcoin (BTC) broke all records with an astonishing twenty-fold increase, making cryptocurrencies one of the hottest topics of 2017 (Nishizawa and Kim, 2017). Late December, search terms related to BTC topped the worldwide charts, which is typically used as proxy for identifying a hype[1]. Reason for many skeptics to believe that this was just another financial bubble waiting to implode, similar to the *Tulip Mania*, *Dot-com Bubble*, and the more recent *Housing Bubble* (Garber, 1989; Cooper et al., 2001; Cheng et al., 2014). Although the prices of most cryptocurrencies indeed have been substantially corrected since the beginning of this year, the coins and their underlying blockchain are increasingly embraced by the established financial markets. Recently, both the *Chicago Board Options Exchanges* (CBOE) and the *Chicago Mercantile Exchange* (CME) launched BTC futures, while *VanEck* considers the introduction of ETFs that mimic the returns of cryptocurrencies (Osipovich, 2017; Russo, 2018). However, little is known about the potential impact on the regulated markets yet, as academic literature regarding cryptocurrencies is scarce.

Yermack (2015) was one of the first researchers to investigate BTC dynamics. In this work, the author examines whether the cryptocurrency could be regarded as a *real currency*. Yermack concludes that, due to the extreme volatile nature as compared to traditional currencies, the coin is hardly usable as a unit of account, nor as store of value. Moreover, the exchange rate of BTC exhibits practically zero correlation with regular currencies. Hence, the asset should be regarded as a speculative instrument rather than as a real currency, according to the author. This conclusion is supported by the work of Baek and Elbeck (2015) and Ciaian et al. (2016), who show that the returns of BTC are solely driven by supply and demand and thus not affected by any economic fundamentals. In addition, Ciaian et al. highlight the short-run impact of speculations on its returns. Although speculative trading is not necessarily an undesirable activity, as it provides liquidity and may absorbs excess risk from risk adverse investors, it also increases volatility and the occurrence of pricing bubbles.

Chu et al. (2015) also noticed the extreme volatile nature of the cryptocurrency and tried to find a parametric distribution which best described its times series. The authors argue that a generalized hyperbolic distribution provides the best fit and used this distribution to predict future volatility and returns. Similar research includes the work of Brière et al. (2015) and Katsiampa (2017), who used volatility modelling to examine BTC's diversification features. The authors shows that the inclusion of even a small proportion of the particular coin may dramatically improve portfolio management, due to its remarkably low correlation with other assets and exceptional average return.

Its suitability for portfolio management has been increasingly researched over the last couple years. Dyhrberg (2016) used a GARCH model to investigate the characteristics of BTC compared to both gold and the US Dollar, with the latter being a pure medium of exchange and the former being a pure store of value. The author highlights that the coin exhibits a few exchange rate

[1] Based on data of Google Trends, which can be publicly accessed on: **website**.

characteristics and reacts significantly to the federal funds rate. The comparison with gold is more accurate, however, as BTC reacts equally to the variables in the model, possesses similar hedging capabilities, and reacts symmetrically to bad and good news. Hence, Dyhrberg classifies the coin somewhere between a currency and gold, suggesting that it might be a proper asset for portfolio management. This suggestion has been empirically tested by Bouri et al. (2017) who used a DCC model to assess its *hedge and safe haven properties*[2]. They conclude that BTC can serve as an effective diversifier for most cases, but that this diversification ability is not constant over time. Moreover, they express concerns about liquidity, as the coin is substantially less liquid than conventional assets. The emergence of related funds and financial derivatives (e.g., future contracts) could, however, significantly improve this pitfall, according to the authors.

Besides the limited quantity, all existing research only considers BTC dynamics, while other cryptocurrencies are being underexposed, which makes it impossible to draw generalized conclusions on the cryptocurrencies market yet. Furthermore, little is known about the actual market dynamics between the conventional equity market and cryptocurrencies, which insight becomes increasingly important as the coins are establishing gradually a position within the regulated markets. This thesis contributes to the literature by attempting to fill this gap in current research. The sample consists of two stock indices (S&P500 and Nikkei 225) and five cryptocurrencies (Bitcoin, DASH, Litecoin, Monero, and Ripple), in order to be able to draw generalizing conclusions. Subsequently, by examining four distinct phenomena in a bivariate setting, which presence is well known from stocks, it becomes possible to expose potential dynamics between cryptocurrencies and the equity market. The following phenomena are being covered:

1. Volatility spillovers
2. Leverage effect
3. Time varying correlation
4. Return predictability

This thesis provides a number of new insights. Firstly, convincing evidence is found indicating that the volatility of cryptocurrencies is highly affected by the dynamics of the equity market, but not vice versa. This one-way volatility spillover is also observed in the direction from BTC to the other coins. Secondly, the results provide no clear evidence for the presence of the traditional asymmetric leverage effect in the returns of cryptocurrencies. However, the findings do provide evidence for a reversed leverage effect in the time series of three particular coins, indicating strong risk seeking behavior. Thirdly, the time varying correlation between the equity market and the cryptocurrencies approximates zero on average and is heavily affected by the volatility of both assets, whereas the time varying correlation between BTC and its peers is considerably higher on average and is mainly event driven. Lastly, the past returns of both stock indices and BTC negatively impact the current returns of the (other) cryptocurrencies, while the effect in opposite

[2] Bouri et al. (2017) refer to "hedge and safe haven properties" as having either an extremely low or negatively correlation with the more regular assets, so it can serve as a safe alternative investment during stressed market conditions. Gold is often classified as being a safe haven.

direction is marginal. However, this (cross) return predictability turned out to improve substantially over longer horizons.

The remainder of this thesis is organized as follows. Section 2 introduces some of the main concepts concerning cryptocurrencies. Section 3 provides an overview of the dataset used and the methodology underlying the sample construction. The four subsequent sections cover the extensive analysis of the earlier introduced phenomena. Section 4 examines the presence of a volatility spillover effect between cryptocurrencies and the equity market. Section 5 assesses the presence of an asymmetric leverage effect. Section 6 investigated the drivers of the potential time varying correlation. Section 7 focuses on the last phenomenon: return predictability. Finally, section 8 concludes with the main empirical findings, implications, and an extensive overview of further research recommendations.

2. Preliminaries

This section provides a brief overview of some of the most important concepts behind cryptocurrencies, in order to establish a sound knowledge needed in the remainder of this thesis. The organization of this section is as follows. Subsection 2.1 describes the fundamentals of *blockchain*, the technique underlying cryptocurrencies. Subsection 2.2 emphasizes on the changes to the original blockchain, which led to the large number of different coins, mostly referred to as *forks*. Finally, the most recent developments regarding cryptocurrency regulation are presented in subsection 2.3.

2.1. Blockchain

Technically, a "blockchain" is a continuously growing chain of digital records, called *blocks*, which are linked and secured using *cryptography* (Narayanan et al., 2016). Each block contains the unique identification code (i.e., a "cryptographic hash") of the previous block, the complete transaction history, and a timestamp. The result is an open, distributed ledger that can record transactions between parties in an efficiently, verifiable, and permanent way (Iansiti and Lakhani, 2017). This distributed ledger is managed by a peer-to-peer network collectively adhering to a protocol for inter-node communication and validating new blocks. Once recorded, the data in a particular block can only be altered through a network majority consensus, which ensures the decentralized nature of the blockchain.

Nakamoto (2008) was the first who invented an application using this technique by introducing the Bitcoin. This became the first digital currency (i.e., "cryptocurrency") solving the *double-spending* problem, without the need of having a central authority. Double-spending entails the potential flaw in digital payments which enables to spend the same token more than once through duplication or falsification. Since every single transaction is recorded and validated by the complete blockchain network, parties can mutually check the authenticity of payments, whereas conventional transfers always require the mutual approval of the two concerning banks.

Another traditional mandate of central banks, monetary policy, is also completely decentralized within the blockchain. By providing computing power (CPU) to the network, so called *miners* are rewarded with tokens of the concerning cryptocurrency. Since the network requires an exponential increasing amount of CPU, the release of new coins (i.e., validating new blocks) is mechanically regulated, making monetary policy a self-fulfilling prophecy (Nakamoto, 2008). Hence, the market value of these coins bears no relation to any macro economic fundamentals, nor the pursued policy of a central bank from a specific country. When considering the value of cryptocurrencies, only the traditional economic law of *supply and demand* seems to apply.

2.2. Forks

Although BTC is still the most widely and frequent traded cryptocurrency, the number of new coins has grown exponentially over the past few years to more than 1,600 (Hileman and Rauchs, 2017). It is important to point out, however, that all these secretions are directly derived from the original BTC blockchain. Hence, the introduction of new cryptocurrencies is usually being referred to as forks, as they represent ramifications of the original network (i.e., like the handle of fork transforms into multiple points). There are two types of forks that can be distinguished: *soft forks* and *hard forks* (Narayanan et al., 2016). The former entails a minor change to a previous blockchain protocol which ensures backwards-compatibility (i.e., communication with older blockchains), while the latter comprises a major change to the protocol which limits compatibility. Examples of hard forks include: Litecoin, Monero, BTC Cash, and BTC Gold. In practice, soft forks are frequently used in the context of *Initial Coin Offerings* (ICO). This form of financing, which is very similar to an IPO, typically launches a new coin, built on an existing blockchain protocol, in order to raise money for new business ideas. Subsequently, the issued tokens can be regarded as shares of the issuing company, without the need of having an underwriting investment bank, nor an expensive team of lawyers. However, because of this unregulated nature, various governments are considering an ICO ban or restriction, with the Chinese ICO ban as most recent development (Vigna, 2017).

2.3. Regulation

The legal status of cryptocurrencies is not unambiguously determined and for most countries yet an unexplored territory. Globally, the opinion among national governments is therefore polarized. The Chinese Central Bank banned the handling of BTC by financial institutions, whereas the Japanese government has accepted the coin as legal tender and eliminated the possibility of double taxation (Narayanan et al., 2016). Due to this widespread uncertainty about legislation, the cryptocurrency market is heavily impacted by regulatory shocks. Furthermore, as trading in cryptocurrencies is non-regulated, without the supervision of a central authority, the securities are not accessible to professional traders, causing the market to be dominated by mostly unsophisticated participants. Low levels of investor sophistication are often accompanied with more exposure to behavioral biases (Calvet et al., 2009). However, the recent introduction of regulated BTC futures might have changed this.

3. Data

This section first describes the databases and software used for the extraction and analysis of the dataset in subsection 3.1. Subsequently, the methodology underlying the sample construction is presented in subsection 3.2. Lastly, some descriptive statistics are highlighted in subsection 3.3.

3.1. Databases and software

This thesis considers various cross-sectional market dynamics based on log returns, which are derived from daily closing prices. Data regarding the stock indices is extracted from *Bloomberg*, whereas data regarding cryptocurrencies is extracted from *CoinMarketCap*. The latter collects and weights current trading prices for a large range of cryptocurrencies, from multiple trading platforms, and therefore provides the most representative and accurate source of information, given the enormous amount of cryptocurrency exchanges. Modelling and programming is done in MATLAB combined with the *Oxford MFE Toolbox* developed by Kevin Sheppard[3].

3.2. Sample construction

The sample consists of two stock indices and five cryptocurrencies, as presented in Table 1, and covers a period ranging from June 2014 to February 2018. The S&P500 and Nikkei 225 are selected based on their broad compositions, liquidity, and geographical presence. Both indices consist of a large amount of stocks representing a broad range of sectors, which is important in order to assess general market dynamics. The reason for choosing a Japanese stock index is threefold. Firstly, Hileman and Rauchs (2017) found that the cryptocurrency user share by region, based on combined wallet and payment provider data, is the highest in Asia-Pacific. Secondly, a substantial part of BTC's trading volume share, measured by national currency, is stemming from Japan (JPY). Thirdly, the Japanese government has accepted the coin as legal tender and eliminated the possibility of double taxation on the trading of cryptocurrencies. Hence, a relatively high adoption rate is to be expected, which makes a greater interdependence with the Japanese equity market more plausible. This in stark contrast to the recent ICO ban by the Chinese government, which made including a Chinese stock index less suitable.

Selection of cryptocurrencies is based on market capitalization and date of introduction to the market. Christoffersen (2012) argues that in order to estimate reliable GARCH parameters, a minimum of 1,000 observations is needed. As a multivariate analysis of stock indices combined with cryptocurrencies will be performed, the total yearly observations per asset are restricted to circa 250 trading days, depending on the specific country. Since the trading of stock indices is restricted to the regulatory trading days of the concerning country, while cryptocurrencies are being traded throughout the whole year. Therefore, the five largest coins, with an introduction in 2014 at the latest, are included in the sample.

[3]The Oxford MFE Toolbox is a financial econometric toolbox which includes a.o. various pre-programmed multivariate autoregressive models and can be freely accessed through its developer's **website**.

Table 1: Overview assets

Type of asset	Security	Description
Stock indices	S&P500 (SP500)	Composed of 500 large American listed companies
	Nikkei 225 (NIKK)	Composed of the 225 most liquid assets listed on TSE
Cryptocurrencies	Bitcoin (BTC)	Started trading in 2009, marketcap: \$30bn - \$340bn
	DASH	Started trading in 2014, marketcap: \$2bn - \$13bn
	Litecoin (LTC)	Started trading in 2011, marketcap: \$1bn - \$21bn
	Monero (XMR)	Started trading in 2013, marketcap: \$1bn - \$8bn
	Ripple (XRP)	Started trading in 2011, marketcap: \$6bn - \$130bn

Notes: This table presents an overview of the sample composition along with a brief description of the distinct securities. The lower and upper bound of the market capitalization range are based on the 52-week low and high trading price of the concerning coin, respectively. TSE means Tokyo Stock Exchange.

Subsequently, an adjustment is needed in order to match the daily return data of the cryptocurrencies to the distinct stock indices. In an efficient market, new information will be incorporated in prices instantaneously, i.e. when the markets are open (Fama et al., 1969). Consequently, information arriving in the weekend will be reflected in the return on Monday and information arriving during public holidays in the return of the first trading day after. Under this assumption, the following equation can be derived which aggregates the daily returns of the cryptocurrencies for the cases described:

$$R_{t,adj} = \sum_{d=0}^{D_t} R_{t-d} \tag{1}$$

where $R_{t,adj}$ represents the adjusted aggregated daily log return, D_t represents total number of missing data points immediately prior to the relevant observation, d represents the missing data point, and R_t represents the raw daily log return of the various cryptocurrencies. For example, the weekend returns ($D_t = 2$) of Saturday and Sunday, will be aggregated in Monday's return.

3.3. Descriptive statistics

From Table 2 can be inferred that all assets have had positive returns on average, with the stock indices marginally and the cryptocurrencies substantially above zero. A similar difference can be observed in the comparison of standard deviations, which highlights the extremely volatile nature of cryptocurrencies. Furthermore, SP500, NIKK and BTC exhibit a negative skewness, whereas the other securities show a positive skewness. The former implies that the chance of having a negative daily return is larger than having a positive one, while the latter implies the opposite. Kurtosis is another descriptor of the shape of the probability distribution and measures the *tailedness*. A higher kurtosis is the result of infrequent extreme deviations, which is clearly visible in the statistics of DASH, LTC, and XRP. The subsequent statistics provide the test results of: (1) Engle's ARCH Test; (2) Jarque-Bera Test; and (3) the augmented Dickey-Fuller Test. The

Table 2: Descriptive statistics

	SP500	NIKK	BTC	DASH	LTC	XMR	XRP
Mean (%)	0.04	0.04	0.21	0.29	0.22	0.38	0.41
Std. dev. (%)	0.79	1.30	3.88	6.83	6.05	7.64	7.29
Skewness	-0.61	-0.18	-0.37	1.42	0.77	0.73	2.98
Kurtosis	6.97	9.01	9.25	18.8	17.8	8.92	44.0
Prob. ARCH-LM	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Prob. Jarque-Bera	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Prob. ADF	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	937	912	1,361	1,361	1,361	1,361	1,361

Notes: This table presents the descriptive statistics of the used dataset in the period ranging from June 2014 to February 2018, grouped by type of asset. "Prob. ARCH-LM" refers to the probability of rejecting the null hypothesis of having no autocorrelation. "Prob. Jarque-Bera" reflects the probability of rejecting the null hypothesis that the data comes from a normal distribution with an unknown mean and variance. "Prob. ADF" denotes the probability of rejecting the null hypothesis that a unit root is present in the time series from the augmented Dickey-Fuller test.

first tests for autocorrelation, the second tests for having a normal distribution, and the third tests for having a unit root (i.e., a systematic pattern that is unpredictable). All three tests have to be rejected in order to perform autoregressive modeling. Finally, the difference in number of observations of the different assets is due to the regulatory difference in trading days between SP500 and NIKK on the one hand, and no limited regulatory trading days for the cryptocurrencies on the other hand.

4. Volatility spillovers

This section investigates the first potential phenomenon: *volatility spillovers*. Subsection 4.1 provides the background literature in order to understand the concept and economical reasoning behind it. Subsection 4.2 provides the used methodology to assess the appearance of volatility spillovers. Subsequently, the empirical results will be discussed in subsection 4.3. Finally, the partial conclusion on the appearance of volatility spillovers in a bivariate model of stock indices combined with cryptocurrencies will be presented in subsection 4.4.

4.1. Emergence of volatility spillovers

Since the international stock market crash of 1987, known as *Black Monday*, there has developed a growing literature on volatility spillovers initiated by Engle et al. (1990). This crash started on the stock exchange of Hongkong, when markets in the West were closed, and eventually affected the exchanges in Europe and the United States, which resulted in the biggest one-day-decline in history. The paper of Engle et al. uses the 1987 crash to assess *market dexterity* (i.e., the accuracy of the incorporation of new relevant information in prices). In an efficient market, asset prices adjust instantaneously and completely in response to new information. Under the assumption that news has only country specific autocorrelation, it should be acting like a heat wave as opposed to a meteor shower. When a country is hit by a heat wave on a specific day, it is very likely that this will continue the days thereafter. However, a heat wave in Asia is most likely not a proper indicator for the weather forecast in the United States. This in contrast to a meteor shower hitting Asia, which will eventually reach the United States through the rotation of the earth. By showing that news in the days around Black Monday acted as a meteor shower, Engle et al. proved the presence of volatility spillovers between markets and thus evidence against market dexterity.

Similar evidence was found by Lin et al. (1994) who showed that the daytime returns of the Tokyo Stock Exchange (TSE) are correlated with the overnight returns of the New York Stock Exchange (NYSE), and vice versa. Other supportive papers investigating volatility spillover effect on various equity markets include Bekaert and Harvey (1997), Ng (2000), Bekaert et al. (2005), and Baele (2005). Attempts to prove volatility spillover effects between exchange rates showed mixed results. Baillie and Bollerslev (1990) studied this effect between the Deutschmark and Japanese Yen, recorded on an hourly basis, and found no clear volatility spillover. However, when examined the same exchange rates on a two weekly basis, as performed by Hong (2001), a strong simultaneous volatility interaction between them was observed.

Rational explanations for the volatility spillover phenomenon are usually sought in the interwovenness of economies, as countries are interdependent through international trade and investments (Lin et al., 1994). In this way, any news about economic fundamentals in one country most likely has implications for its trading partners. From a more behavioral perspective, speculative trading and noise trading are named as potential explanations, since fads and a herd instinct are found to be transmittable across borders (Black, 1986; De Long et al., 1990). When examining the volatility spillover effect in the context of cryptocurrencies, the behavioral explanation is the most plausible, as cryptocurrencies are supranational and their value is not based on any underlying economic fundamentals. This research on the presence of volatility interaction between cryptocurrencies and the equity market can therefore contribute to the ongoing debate about the speculative nature of these coins.

4.2. Methodology: BEKK-GARCH

To assess the volatility interaction between cryptocurrencies and the equity market, a multivariate model is required. This research uses a general multivariate GARCH model given by the following equations (Daníelsson, 2011):

$$\epsilon_t = H_t^{1/2} z_t \tag{2}$$

$$z_t \sim (0, I_k) \tag{3}$$

where ϵ_t represents the $(k \times 1)$ vector of innovations for k assets at time t, H_t represents the $(k \times k)$ conditional variance-covariance matrix, and z_t represents the k-dimensional return shock following an i.d.d. process with mean zero and covariance matrix equal to the identity matrix I_k. From equation (2) and the properties of z_t displayed in equation (3) it follows that:

$$\epsilon_t \sim (0, H_t) \tag{4}$$

Subsequently, a BEKK-specification is used for the parameterization of H_t, as introduced by Engle and Kroner (1995). In this MV-GARCH model, the matrix of conditional covariances is a function of the outer product of lagged innovations and lagged conditional covariances, each pre-multiplied and post-multiplied by a parameter matrix (Daníelsson, 2011). This results in a quadratic function that is guaranteed to be positive semi-definite, which is one of the key features of BEKK, since this guarantees the existence of maxima and minima needed for optimization. Moreover, the model allows for interactions between different asset returns and volatilities, and is relatively parsimonious in terms of parameters required, compared to alternative multivariate models. The specification of BEKK is given by:

$$H_t = \Omega'\Omega + A'\epsilon_{t-1}\epsilon'_{t-1}A + B'H_{t-1}B \tag{5}$$

where Ω is a lower triangular matrix of constants, A and B are $(k \times k)$ matrices of parameters. By considering a BEKK(1,1,2) model (i.e., one lag and $k = 2$), equation (5) is fully written as:

$$\begin{aligned} H_t = \begin{bmatrix} h_{t,11} & h_{t,12} \\ h_{t,21} & h_{t,22} \end{bmatrix} &= \begin{bmatrix} \omega_{1,1} & \omega_{2,1} \\ 0 & \omega_{2,2} \end{bmatrix} \begin{bmatrix} \omega_{1,1} & 0 \\ \omega_{2,1} & \omega_{2,2} \end{bmatrix} \\ &+ \begin{bmatrix} \alpha_{1,1} & \alpha_{2,1} \\ \alpha_{1,2} & \alpha_{2,2} \end{bmatrix} \begin{bmatrix} \epsilon^2_{t-1,1} & \epsilon_{t-1,1}\epsilon_{t-1,2} \\ \epsilon_{t-1,2}\epsilon_{t-1,1} & \epsilon^2_{t-1,2} \end{bmatrix} \begin{bmatrix} \alpha_{1,1} & \alpha_{1,2} \\ \alpha_{2,1} & \alpha_{2,2} \end{bmatrix} \\ &+ \begin{bmatrix} \beta_{1,1} & \beta_{2,1} \\ \beta_{1,2} & \beta_{2,2} \end{bmatrix} \begin{bmatrix} h_{t-1,11} & h_{t-1,12} \\ h_{t-1,21} & h_{t-1,22} \end{bmatrix} \begin{bmatrix} \beta_{1,1} & \beta_{1,2} \\ \beta_{2,1} & \beta_{2,2} \end{bmatrix} \end{aligned} \tag{6}$$

where the elements of A reflect the effect of lagged innovations on current volatility (i.e., ARCH effect) and the elements of B reflect the effect of lagged volatility (i.e., GARCH effect). The diagonal elements $a_{1,1}$, $a_{2,2}$, $b_{1,1}$, and $b_{2,2}$ measure the direct effects on asset's own volatility, while the off-diagonal elements $a_{2,1}$, $a_{1,2}$, $b_{2,1}$, and $b_{1,2}$ measure the cross-spillover effects on the other asset's volatility. For simplicity, by suppressing the time subscripts and the GARCH terms, it follows from equation (6) that the conditional variance $\sigma^2_{t,ii}$ is defined by:

$$h_{11} = \omega_{1,1} + \alpha^2_{1,1}\epsilon^2_1 + 2\alpha_{1,1}\alpha_{2,1}\epsilon_1\epsilon_2 + \alpha^2_{2,1}\epsilon^2_2 \tag{7}$$

$$h_{22} = \omega_{2,2} + \alpha^2_{1,2}\epsilon^2_1 + 2\alpha_{1,2}\alpha_{2,2}\epsilon_1\epsilon_2 + \alpha^2_{2,2}\epsilon^2_2 \tag{8}$$

while the conditional covariance $\sigma_{t,12}$, in simplified form, is defined according:

$$h_{12} = \omega_{2,1} + \alpha_{1,1}\alpha_{1,2}\epsilon_1^2 + (\alpha_{2,1}\alpha_{1,2} + \alpha_{1,1}\alpha_{2,2})\epsilon_1\epsilon_2 + \alpha_{2,1}\alpha_{2,2}\epsilon_2^2 \tag{9}$$

The elements of Ω, A, and B are estimated by *Maximum Loglikelihood Estimation* (MLE) which uses linear programming to optimize each parameter and is specified as (Engle and Kroner, 1995):

$$\max \mathcal{L} = \max \sum_{t=1}^{T} \left[\frac{k}{2} \ln 2\pi - \frac{1}{2} \ln |H_t| - \frac{1}{2} \epsilon_t' H_t^{-1} \epsilon_t \right] \tag{10}$$

where $\mathcal{L}$ represents the loglikelihood and T represents the total number of observations within the time series.

One drawback of BEKK is that many parameters are often found to be statistically insignificant, which is an indication for overparameterization (Daníelsson, 2011). Another important drawback is that, despite its parsimonious nature, the various estimated parameters are hard to interpret. Therefore, visualization through *News Impact Curve* (NIC) plots is used for interpretation purposes, following Engle and Ng (1993). These plots show the impact of past return shocks z_{t-1} (news) on current volatility, In a multivariate setting, *News Impact Surfaces* (NIS) are defined accordingly (Kroner and Ng, 1998; Asai and McAleer, 2009):

$$NIS(z_t) = H_{t+1}(z_t | H_t = \overline{H}) - H_{t+1}(0 | H_t = \overline{H}) \tag{11}$$

where z_t denotes the k-dimensional return shock, and $\overline{H}$ refers to the unconditional variance-covariance matrix of the model. To allow for easy interpretation, rather than plotting the full surface for a range of shocks, only NICs for two opposing states are plotted, following Bollerslev et al. (2018):

$$z_{t,1} = [-4 : 0.1 : 4] \tag{12}$$

$$z_{t,1} = z_{t,2} \tag{13}$$

$$z_{t,1} = -z_{t,2} \tag{14}$$

where equation (13) refers to a situation with return shocks in equal direction and equation (14) to a situation with shocks in opposite direction.

4.3. Empirical results

Table 3 presents the parameter estimations for fourteen distinct BEKK(1,1,2) models. Panel A contains five bivariate models combining SP500 with the cryptocurrencies, Panel B combines NIKK with cryptocurrencies, and Panel C contains four bivariate models combining BTC with the other coins. Ordering in the models is set in accordance to the sequence previously mentioned. Since the focus of this section is on spillover effects, only the off-diagonal elements will be highlighted.

Table 3: Parameter estimations BEKK-GARCH

Parameter	Panel A: SP500 vs. Coin					Panel B: NIKK vs. Coin					Panel C: BTC vs. Coin			
	BTC	DASH	LTC	XMR	XRP	BTC	DASH	LTC	XMR	XRP	DASH	LTC	XMR	XRP
$\omega_{1,1}$	-0.0023***	0.0022**	0.0022***	-0.0021***	-0.0021***	0.0029***	0.0026***	-0.0026***	-0.0024***	-0.0026***	-0.0061***	-0.0047	0.0062***	-0.0054***
	(0.0004)	(0.0009)	(0.0004)	(0.0005)	(0.0003)	(0.0007)	(0.0008)	(0.0005)	(0.0005)	(0.0006)	(0.0016)	(0.0036)	(0.0019)	(0.0014)
$\omega_{2,1}$	0.0074***	0.0043	-0.0013	0.0003	0.0005	0.0017	0.0034	0.0016	0.0019	-0.0018	0.0024	-0.0079***	0.0049	-0.0022
	(0.0022)	(0.0038)	(0.0003)	(0.0043)	(0.0600)	(0.0025)	(0.0045)	(0.0023)	(0.0109)	(0.0074)	(0.0133)	(0.0030)	(0.0031)	(0.0029)
$\omega_{2,2}$	0.0000	0.0184	0.0180***	-0.0233***	-0.0177***	-0.0089***	0.0199***	-0.0178***	0.0241***	0.0238***	0.0161**	-0.0076**	0.0147***	-0.0183***
	(0.0000)	(0.0341)	(0.0050)	(0.0042)	(0.0043)	(0.0031)	(0.0045)	(0.0045)	(0.0034)	(0.0052)	(0.0074)	(0.0031)	(0.0026)	(0.0051)
$\alpha_{1,1}$	0.4507***	0.4260***	0.4236***	0.4515***	0.4296***	0.3572***	0.3211***	0.3769***	0.3850***	0.3660***	0.3858***	0.2499***	0.4096***	0.3692***
	(0.0591)	(0.1064)	(0.0587)	(0.0592)	(0.0600)	(0.0617)	(0.0692)	(0.0557)	(0.0512)	(0.0525)	(0.0874)	(0.0836)	(0.0424)	(0.0450)
$\alpha_{2,1}$	0.0009	0.0036	0.0032	0.0017	-0.0021	0.0152	0.0058	0.0042	0.0037	0.0137***	-0.0062	-0.0144	-0.0034	0.0032
	(0.0028)	(0.0029)	(0.0032)	(0.0088)	(0.0021)	(0.0170)	(0.0050)	(0.0036)	(0.0044)	(0.0043)	(0.0570)	(0.0479)	(0.0065)	(0.0117)
$\alpha_{1,2}$	-0.0319***	0.3958	0.1621	0.6868	0.4218	0.0178	-0.4998**	0.0046	-0.2658	-0.2602	-0.1370	-0.2963*	0.1512*	-0.1962
	(0.0000)	(1.3947)	(0.3288)	(0.4663)	(0.2891)	(0.0130)	(0.1994)	(0.0091)	(0.2713)	(0.1686)	(0.1960)	(0.1605)	(0.0776)	(0.1237)
$\alpha_{2,2}$	0.3992***	0.4824	0.3537***	0.2538***	0.4386***	0.4318***	0.4869***	0.3713***	0.2520***	0.6190***	0.4881***	0.4705***	0.2946***	0.5751***
	(0.0000)	(0.4809)	(0.0651)	(0.0842)	(0.0940)	(0.0742)	(0.1245)	(0.0714)	(0.0667)	(0.1133)	(0.1375)	(0.1171)	(0.0379)	(0.1482)
$\beta_{1,1}$	-0.8480***	0.8673***	0.8608***	0.8543***	0.8713***	0.9083***	0.9273***	0.9078***	0.9106***	0.9108***	0.9167***	0.9389***	0.9104***	0.9293***
	(0.0380)	(0.0911)	(0.0368)	(0.0378)	(0.0304)	(0.0321)	(0.0330)	(0.0246)	(0.0204)	(0.0237)	(0.0371)	(0.0362)	(0.0209)	(0.0149)
$\beta_{2,1}$	0.0062	-0.0019*	-0.0017	0.0004	0.0009	-0.0074	-0.0024*	-0.0012	-0.0007	-0.0067***	0.0084	0.0260	0.0033	0.0003
	(0.0112)	(0.0010)	(0.0021)	(0.0028)	(0.0011)	(0.0074)	(0.0014)	(0.0012)	(0.0034)	(0.0023)	(0.0387)	(0.0199)	(0.0023)	(0.0008)
$\beta_{1,2}$	-0.2487	-0.1888	0.0834	-0.3394	-0.1357	-0.0062	0.1428***	0.0210	0.1310	0.0595	0.0845	0.0359	-0.0424	0.0754
	(0.4087)	(0.4035)	(0.2299)	(0.2916)	(0.1103)	(0.0109)	(0.0503)	(0.0233)	(0.1025)	(0.1270)	(0.1132)	(0.0757)	(0.0386)	(0.0502)
$\beta_{2,2}$	0.9165***	0.8626**	0.9077***	0.9311***	0.8764***	0.9013***	0.8603***	0.9069***	0.9310***	0.7840***	0.8447***	0.9046***	0.9325***	0.7954***
	(0.0224)	(0.3410)	(0.0277)	(0.0236)	(0.0437)	(0.0328)	(0.0405)	(0.0254)	(0.0167)	(0.0475)	(0.1075)	(0.0566)	(0.0145)	(0.0908)
$\mathcal{L}$	5,021	4,494	4,591	4,289	4,596	4,374	3,879	3,989	3,680	3,964	4,783	5,257	4,551	4,869
Observations	937	937	937	937	937	912	912	912	912	912	1,361	1,361	1,361	1,361

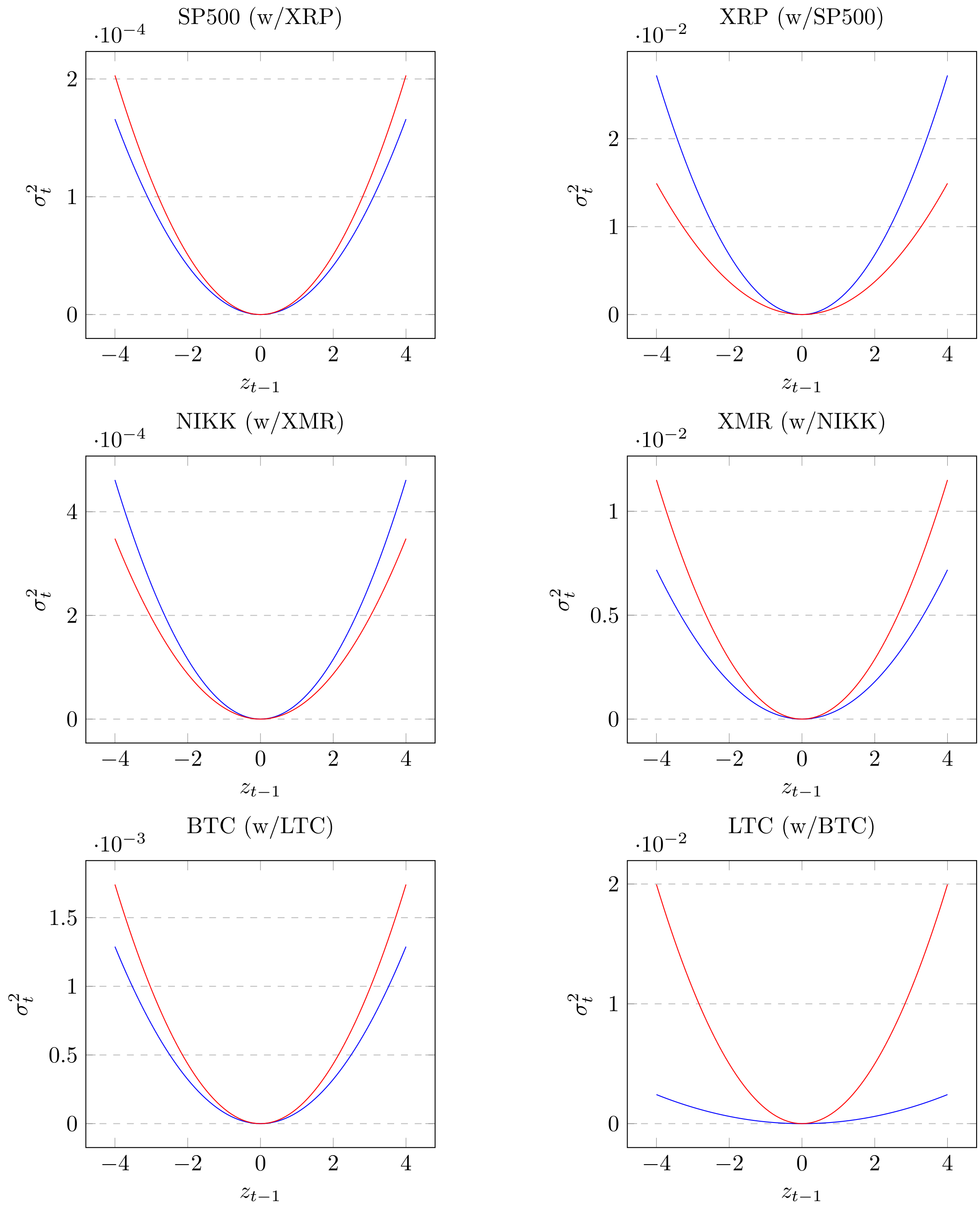
Notes: This table presents the parameter estimations for fourteen distinct BEKK(1,1,2) models as defined by equation (5). Panel A shows all bivariate models combining SP500 with the cryptocurrencies. Panel B shows all bivariate models combining NIKK with the cryptocurrencies. Panel C shows all bivariate models combining BTC with the other coins. Bivariate ordering is done according to the sequence just mentioned. Numbers between the parentheses denote the standard errors of the concerning parameters. The asterisks ***, **, and * denote the statistical significance on a 1%, 5%, and 10% level, respectively. As proof of feasible convergence, all models meet the requirement of having a higher $\mathcal{L}$ than its diagonal-BEKK compeer.

From Panel A can be inferred that parameter $\alpha_{2,1}$ is both economical small and highly insignificant for all models. Hence, the presence of a return shock spillover effect in the direction from cryptocurrencies to SP500 seems unfeasible. On the contrary, parameter $\alpha_{1,2}$ is, except for BTC, economical large and positive with smaller standard errors in general. This indicates the presence of a positive return shock spillover effect in the direction from SP500 to the cryptocurrencies. The NIC plots, presented in the top row of Figure 1, visualize this difference in impact. The variance σ^2 of SP500 is hardly affected by a past return shock z_{t-1} in opposite direction of XRP, as illustrated by the marginal shift of the red line. Whereas the variance of XRP is highly affected by a change in the shock direction of SP500, as illustrated by the jump of the red line. Furthermore, the large difference in variance size is worth noting. Parameters $\beta_{2,1}$ and $\beta_{1,2}$, which reflect the volatility spillover, show a similar picture. The former is both economical small and highly insignificant for most models, while the latter seems to show, except for LTC, a strong negative cross spillover effect. This indicates the presence of a negative volatility spillover effect in the direction from SP500 to the cryptocurrencies.

The Asian market shows somewhat more mixed results, as can be seen in Panel B. Parameter $\alpha_{2,1}$ remains economical small but with substantial smaller standard errors in all five models combining NIKK with cryptocurrencies. Nevertheless, the presence of a return shock spillover effect in the direction from cryptocurrencies to NIKK seems unlikely. In the opposite direction, parameter $\alpha_{1,2}$ is economical large and negative for DASH, XMR, and XRP, while small and positive for BTC and LTC. This indicates a weaker presence of a negative return shock spillover effect in the direction from NIKK to the cryptocurrencies, as illustrated by the NIC plots in the mid row of Figure 1. The red line in the XMR plot makes a big jump compared to the red line in the NIKK plot, but the difference is smaller than in Panel A. The volatility spillover effect is also less pronounced in both directions. Parameter $\beta_{2,1}$, which reflects the spillover effect in the direction from cryptocurrencies to NIKK, is economical small, negative, and relatively significant for all models. In the opposite direction, parameter $\beta_{1,2}$ is considerably larger and positive, but the effect is less pronounced and has an opposite sign compared to Panel A. However, this still indicates the presence of a small, positive volatility spillover effect in the direction from NIKK to the cryptocurrencies.

Between BTC and the other coins some interaction can be inferred, as presented in Panel C. The effect remains one-way traffic though. Parameter $\alpha_{2,1}$ is economical small and highly insignificant for all four models, while parameter $\alpha_{1,2}$ is economical large and negative, with acceptable standard errors. Hence, the presence of a large negative return shock spillover effect in the direction from BTC to the other coins seems feasible, but not vice versa. This is visualized in the bottom row of Figure 1, which exhibits a big jump of the red line in the LTC plot whereas the effect of an opposite return shock in the BTC plot is only marginal. The volatility spillover effect is, like Panel A and B, less pronounced in both directions. Parameter $\beta_{2,1}$ is economical small, positive and insignificant for all four models. Parameter $\beta_{1,2}$ is somewhat larger and positive, except for XMR, with smaller standard errors for all models. Nevertheless, this provides an indication for the presence of a small, positive volatility spillover effect from BTC to the other coins.

Figure 1: News Impact Curves: BEKK-GARCH



Notes: This figure shows the News Impact Curves (NIC) for three models (Panel A, B, and C) based on the off-diagonal elements of BEKK-GARCH in Table 3 and are derived from the full surfaces (NIS) outlined in equation (11). Panel A, B, and C are represented in the top, mid, and bottom row, respectively. NICs show the impact of past return shocks z_{t-1} on the current variance σ_t^2 of the assets. The blue line highlights shocks in equal direction, while the red line illustrates the impact of return shocks in opposite direction.

4.4. Conclusion: volatility spillovers

This section investigated the presence of a volatility spillover effect in a bivariate setting combining SP500 with cryptocurrencies, NIKK with cryptocurrencies, and BTC with the other coins. The empirical results provide evidence for the dual presence of a positive return shock spillover effect and a negative volatility spillover effect in the direction from SP500 to the cryptocurrencies, but not vice versa. Hence, it can be concluded that the volatility of cryptocurrencies is highly affected by the dynamics of SP500. Return shocks of SP500 increase the volatility on the cryptocurrency market, while an increase in volatility of SP500 decreases the volatility of cryptocurrencies. The volatility interaction between NIKK and cryptocurrencies is quite similar but less pronounced and the effect occurs in opposite direction. Return shocks of NIKK decrease volatility, while an increase in volatility has a positive effect on the volatility of cryptocurrencies. This co-movement in volatility and negative impact of return shocks on volatility can also be observed in the models combining BTC with the other coins. Return shocks of BTC negatively affect the volatility of its peers, whereas volatility exhibits a positive spillover effect. These dynamics within the cryptocurrency market can possibly be explained by BTC's dominant position, making it the most important benchmark for most cryptocurrency investors. In this way, the volatility of BTC serves as an important indicator for overall risk within the market, igniting a positive spillover effect.

5. Leverage effect

This section examines the second potential phenomenon: *leverage effect*. In subsection 4.2 BEKK-GARCH was introduced which offers the possibility of including asymmetric innovations in the model. However, inclusion is only meaningful when this leads to an improvement of the bivariate models in terms of loglikelihood. Examining the leverage effect in a univariate setting can help in making this assessment. The remainder of this section is organized as follows. Subsection 5.1 provides the background literature and introduction of the concept. Subsequently, the model to assess the appearance of the effect in the used dataset is outlined in subsection 5.2. Finally, the ensuing empirical results and implications will be discussed in subsections 5.3 and 5.4, respectively.

5.1. Leveraging: mechanically or behavioral

The term "leverage effect" was introduced in the work of Black (1976) and Christie (1982), who provided also a first rational explanation for this phenomenon. As the stock price of a company declines, it becomes mechanically more leveraged since its debt level remains stable while the equity value decreases. Higher leverage translates into more risk, which has naturally an increase in volatility as a consequence. An alternative economic interpretation reverses the causality by proposing a *volatility feedback loop* (French et al., 1987; Campbell and Hentschel, 1992). Increased volatility requires a higher rate of return, which only can be realized through a discount on the asset price. This stock price decline results, like in the former explanation, mechanically in more leverage and thus an increase in volatility, which rounds the feedback loop. Attempts to find the actual direction of causality, using both low and high frequency data, provide support for the dual presence of both explanations (Bekaert and Wu, 2000; Bollerslev et al., 2006).

Although the mechanism seems to work equal in both directions (i.e., stock price increases and decreases), a.o. French et al. (1987), Schwert (1990), Nelson (1991), and Engle and Ng (1993) document the asymmetric effect of news on volatility: negative innovations increase the volatility of an asset more than positive innovations of the same size. The *prospect theory*, developed by Kahneman and Tversky (1979), provides a behavioral explanation for this observation. Under this framework, potential outcomes are treated as losses and gains depending on a certain (arbitrary) reference point. Subsequently, the value function is defined by deviations from this reference point and is steeper for losses than for gains, typically known as *loss aversion*. Hence, a stock price decline is weighted more heavily than a stock price increase, resulting in the asymmetric effect of news on volatility.

Despite the uncertainty about its origin, there is a broad consensus in the literature about the presence of an asymmetric leverage effect in the equity market (Ait-Sahalia et al., 2013). Whether this effect is also present in the time series of cryptocurrencies is yet an undiscovered field of research. None of the above mentioned rational explanations seems applicable to cryptocurrencies, since there are no economic fundamentals underlying their market value. Hence, the potential observation of an asymmetric leverage effect in the cryptocurrency data can only be attributed to more irrational behavior such as speculative trading, noise trading, and the prospect theory.

5.2. Methodology: GJR-GARCH

To assess the presence of an asymmetric leverage effect in the used dataset, an extension to the standard univariate GARCH model is used, as proposed by Glosten et al. (1993). This model captures the effect by including an indicator I_{t-1} reflecting the sign of the past innovation ϵ_{t-1}:

$$I_{t-1} = \begin{cases} 1, & \text{if } \epsilon_{t-1} < 0 \\ 0, & \text{if } \epsilon_{t-1} \geq 0 \end{cases} \tag{15}$$

which is included in the univariate, one lagged GJR(1,1,1) model according:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \alpha\gamma I_{t-1}\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{16}$$

where σ^2 denotes the variance, ω is a constant, α reflects the impact of lagged innovations on current volatility, γ captures the leverage effect, and β reflects the impact of lagged on current volatility. Subsequently, these parameters are estimated using a similar method outlined in equation (10), defined by:

$$\max \mathcal{L} = \max \sum_{t=1}^{T} \Big[-\frac{1}{2}\ln 2\pi - \frac{1}{2}\ln \sigma_t^2 - \frac{1}{2}\frac{\epsilon_t^2}{\sigma_t^2} \Big] \tag{17}$$

where $\mathcal{L}$ denotes the loglikelihood and T represents the total number of observations within the time series.

The found parameters are used for visualization of the asymmetric leverage effect by computing univariate NICs, which can be directly derived from equation (16) (Engle and Ng, 1993):

$$NIC(z_t) = \alpha\overline{h}z_t^2 + \alpha\gamma I_t\overline{h}z_t^2 \tag{18}$$

where $\overline{h}$ refers to the unconditional variance of the model and return shock $z_t = [-4 : 0.1 : 4]$.

5.3. *Empirical results*

Table 4 provides the parameter estimations of the univariate GJR model for the stock indices and cryptocurrencies. Since the focus of this section is on the leverage effect, only values of parameter γ will be highlighted. In line with previous research, for both SP500 and NIKK parameter γ is economical large, positive, and highly significant. Hence, the presence of an asymmetric leverage effect in these assets seems very plausible. This asymmetry is nicely visualized by means of a NIC plot in Figure 2. As illustrated on the left, SP500 reacts more heavily on negative past return shocks z_{t-1} than on their positive counterparts.

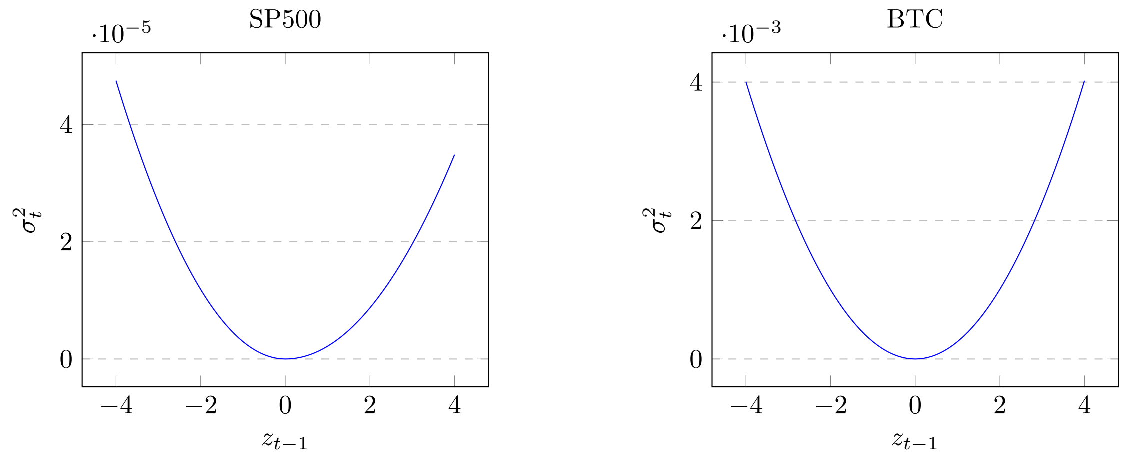
Table 4: Parameter estimations GJR-GARCH

Parameter	SP500	NIKK	BTC	DASH	LTC	XMR	XRP
ω	0.0000***	0.0000***	0.0000***	0.0004***	0.0002***	0.0003***	0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	0.0348***	0.0008	0.1666***	0.3283***	0.1222***	0.1606***	0.7082***
	(0.0124)	(0.0110)	(0.0164)	(0.0277)	(0.0124)	(0.0153)	(0.0441)
β	0.7218***	0.8290***	0.8355***	0.6450***	0.8654***	0.8453***	0.4966***
	(0.0357)	(0.0160)	(0.0107)	(0.0234)	(0.0104)	(0.0114)	(0.0105)
γ	0.3620***	0.2678***	-0.0043	-0.0376	-0.0600***	-0.1070***	-0.4096***
	(0.0593)	(0.0324)	(0.0161)	(0.0368)	(0.0119)	(0.0158)	(0.0511)
$\mathcal{L}$	3,363	2,814	2,711	1,920	2,091	1,673	2,119
Observations	937	912	1,361	1,361	1,361	1,361	1,361

Notes: This table provides the parameter estimations for the univariate GJR-GARCH model as defined by equation (16). Numbers between the parentheses provide the standard errors of the concerning parameters. The asterisks ***, **, and * denote the statistical significance on a 1%, 5%, and 10% level, respectively. As proof of feasible convergence, all models meet the requirement of having a higher $\mathcal{L}$ than its standard univariate GARCH compeer (i.e., without the inclusion of asymmetric innovations).

The cryptocurrencies show a completely different picture. Parameter γ is for both BTC and DASH economical small, negative, and highly insignificant. LTC and XMR show a slightly larger and significant parameter value, while XRP exhibits an economical large, negative, and highly significant leverage parameter. While $\gamma > 0$ captures the regular leverage effect, a negative coefficient would imply the exact opposite. However, the literature provides neither a rational explanation

Figure 2: News Impact Curves: GJR-GARCH



Notes: This figure shows the News Impact Curves (NIC) for SP500 and BTC based on the univariate GJR-GARCH parameter estimations in Table 4. NICs show the impact of past return shocks z_{t-1} on the current variance σ_t^2 of the assets and are computed according to equation (18).

for a reversed leverage effect, nor a behavioral explanation. Therefore, conclusions will be drawn solely based on the parameter estimations for BTC and DASH, making the presence of a regular asymmetric leverage effect in the time series of cryptocurrencies unfeasible. This is also visualized in the right plot of Figure 2, which exhibits an almost perfect symmetry for BTC. The substantial difference in variance size between the stock index and cryptocurrency, resulting from the return shocks, is also worth noting.

5.4. Conclusion: leverage effect

This section investigated the presence of an asymmetric leverage effect with the purpose of potentially improving the bivariate BEKK models of section 4 by including asymmetric innovations. Based on the empirical results, it can be concluded that both stock indices SP500 and NIKK exhibit a strong traditional leverage effect, which is supported by numerous empirical findings and the economical reasoning in relevant literature, as displayed in subsection 5.1. The indices are composed of real company stocks with underlying economic fundamentals. Hence, it seems evident that the mechanical leveraging effect works in an equal manner for both real stocks and stock indices. This reasoning does not apply for cryptocurrencies, because of the lack of these economic fundamentals. The empirical finding that the presence of an asymmetric leverage effect seems not feasible in the times series of BTC, DASH, LTC, XMR, and XRP, comes therefore not entirely as a surprise. The prospect theory provides a possible explanation for the significant negative coefficients of LTC, XMR, and XRP, which could indicate strong *risk seeking* or *return chasing* behavior in the cryptocurrency market, since a negative leverage coefficient implies a stronger impact of positive return shocks on volatility. Although this reasoning seems plausible, a more profound analysis is beyond the scope of this thesis. To conclude, this section proved the presence of an asymmetric leverage effect in the time series of the stock indices, but not in those of cryptocurrencies, making the inclusion of asymmetric innovations in the bivariate BEKK models not desirable.

6. Time varying correlation

This section investigates the third potential phenomenon: *time varying correlation*. From the BEKK models outlined in section 4, the dynamic variance-covariance matrices can be extracted. This entails the opportunity to derive the time varying correlation for all bivariate models included in Table 3 and to identify its most important drivers. The remainder of this section is organized as follows. Subsection 6.1 provides an overview of the existing literature regarding the time varying correlation between various securities and its implications for modern portfolio theory. Subsection 6.2 discusses the correlation extraction and regression methods. Finally, subsections 6.3 and 6.4 emphasize on the empirical results and the resulting partial conclusion on time varying correlation, respectively.

6.1. Drivers of time varying correlation

Understanding return correlation dynamics between different asset classes has become the top priority in portfolio management, since Markowitz (1952) introduced his *Modern Portfolio Theory*. Previously, conservative investors would include low volatility assets in their portfolios to realize stability in their aggregated returns. Markowitz showed, however, that by combining risky assets with low or negative correlations, the same (or lower) volatility with higher (or the same) returns could be achieved. Hence, in order to realize optimal diversification, the portfolio weights of the included assets should depend on their own volatility and the correlation between them.

Following this reasoning, Levy and Sarnat (1970), Grubel and Fadner (1971), and Lessard (1974), strongly advocated international diversification within equity portfolios on basis of low correlation between national markets. However, the turmoil on the international financial markets (e.g., "Black Monday") in the following years made painfully clear that international diversification provides no guarantee in times of widespread economic downturn (Lin et al., 1994). Therefore, questions were raised about the usefulness of portfolio diversification based on correlations, as its benefits are apparently not forthcoming at times investors need them the most. This ambiguity in the literature was not so surprising as the standard model for diversification was a static one-period mean-variance framework at the time (French and Poterba, 1991; Tesar and Werner, 1995). In response, Ang and Bekaert (2002) highlighted the importance of frequently adjusted portfolio weights, by analyzing the impact of time varying correlations on asset allocation in a dynamic portfolio allocation problem.

Literature concerning the drivers of time varying correlations mention various potential factors affecting the correlation between certain assets. Lin et al. (1994) find that volatility increases correlation between markets, while Longin and Solnik (1995, 2001) and Erb et al. (1994) state that high volatility in itself does not seem to lead to an increase in conditional correlation. They find that correlation is mainly affected by the market trend: correlation strongly increases in simultaneous *bear markets* and remains rather stable in *bull markets*. All of these papers investigated the time varying correlation between national equity markets. Therefore, it might be interesting to find out whether the same drivers affect the time varying correlation between cryptocurrencies and the equity market. As cryptocurrencies have a supranational nature, it seems unfeasible that correlation is affected by market trends, while the volatility argument remains plausible. Assessing which factors drive the time varying correlation could contribute to the improvement of portfolio management involving cryptocurrencies.

6.2. Methodology: OLS

The time varying correlation can be directly derived from the earlier discussed BEKK model, as defined by equation (6). From the dynamic variance-covariance matrix H_t, the correlation $\rho_{t,12}$ at time t can be extracted according:

$$\rho_{t,12} = \frac{h_{t,12}}{\sqrt{h_{t,11}h_{t,22}}} = \frac{\sigma_{t,12}}{\sigma_{t,11}\sigma_{t,22}} \tag{19}$$

where $\sigma_{t,12}$ denotes the covariance between assets, while $\sigma_{t,11}$ and $\sigma_{t,22}$ reflect the volatility of the distinct assets.

Subsequently, an *Ordinary Least Squares* (OLS) regression is performed to examine which factors drive the time varying correlation $\rho_{t,12}$ between cryptocurrencies mutually and between cryptocurrencies and the stock indices. The regression is defined by:

$$\rho_{t,12} = c + \gamma_1 r_{t,1} + \gamma_2 r_{t,2} + \gamma_3 \sigma_{t,11} + \gamma_4 \sigma_{t,22} + \gamma_5 d_1 + \gamma_6 d_2 + \gamma_7 d_3 + \gamma_8 d_4 + \epsilon_t \tag{20}$$

where c is a constant, $\gamma_{1:8}$ denotes the concerning regression coefficient, $r_{t,i}$ refers to the log return of the i^{th} asset, $\sigma_{t,ii}$ denotes the volatility, and $d_{1:4}$ is one of four dummy variables representing the specific events outlined in Table 6. These events are selected on basis of their likely impact on the cryptocurrency market.

6.3. Empirical results

Table 5 provides the summary statistics of the time varying correlation for fourteen distinct models equal to those documented in section 4. It stands out that the average correlation between both stock indices and the cryptocurrencies is almost zero, while the correlation between cryptocurrencies mutually is economical large. In addition, the table highlights substantial fluctuations of the time varying correlation for all models, with standard deviations between 15-30% on a daily basis. This stresses the importance of modeling time varying correlation in order to make adequate adjustments to portfolio weights.

Subsequently, the results of the OLS regression on the time varying correlation are presented

Table 5: Time varying correlation summary statistics

Panel	BTC	DASH	LTC	XMR	XRP
SP500	0.0060	0.0904	0.0074	0.0456	0.0356
	(0.1959)	(0.2218)	(0.1801)	(0.1465)	(0.2004)
NIKK	-0.0088	0.0749	-0.0189	0.0237	0.0039
	(0.2147)	(0.2087)	(0.1768)	(0.1578)	(0.2108)
BTC	-	0.3302	0.6627	0.3796	0.2382
		(0.2930)	(0.2042)	(0.2472)	(0.2560)

Notes: This table provides the average time varying correlation between June 2014 and February 2018 as defined in equation (19). Numbers between the parentheses denote the standard deviation of the correlation. Used models are equal to those outlined in Table 3.

in Table 6. Panel A contains five models combining SP500 with the cryptocurrencies, Panel B combines NIKK with the cryptocurrencies, and Panel C contains four models combining BTC with the remaining coins. From Panel A can be inferred that both the log return of SP500 and the cryptocurrencies exhibit no significant explanatory power for the time varying correlation. Volatility, on the other hand, seems to have an economical large, positive, and highly significant impact, in particular the volatility of SP500. It should be noted, however, that volatility of assets affects the correlation by construct, as illustrated in equation (19). Although the former slightly weakens the conclusion, the general trend remains clear. The impact of the selected events is less evident and economical smaller. The introduction of BTC futures and BTC Gold seems to have had no effect, while the Chinese ICO ban and the introduction of BTC Cash seem to have increased the correlation between SP500 and the cryptocurrencies marginally.

Panel B provides a similar picture. It can be inferred that both the impact from the log return of NIKK and cryptocurrencies on correlation seems unfeasible. The coefficients of volatility are again economical large, but of an opposite sign for NIKK. Hence, the volatility of NIKK seems to decrease the time varying correlation, while the volatility of the cryptocurrencies seems to have a positive impact. This panel also proves that the impact of volatility on correlation is not just mechanically, since Table 5 highlights a negative average correlation between NIKK and LTC, despite the positive volatility coefficients. The introduction of BTC futures and the Chinese ICO ban seem to have increased the correlation between NIKK and the cryptocurrencies, while the introduction of BTC Gold clearly had a negative impact. The introduction of BTC Cash exhibits mixed results.

Finally, from Panel C can be inferred that the log returns of BTC have a positive influence on the correlation with its peers, while the returns of the other coins have a negative impact. In addition, the volatility of BTC seems to have an economical large, significant, and positive impact, while the volatility of its peers exhibits a significant negative relation with the correlation. The impact of the selected events seems, as expected, of much greater importance for the time varying correlation than in the other panels. The introduction of BTC futures and the Chinese ICO ban

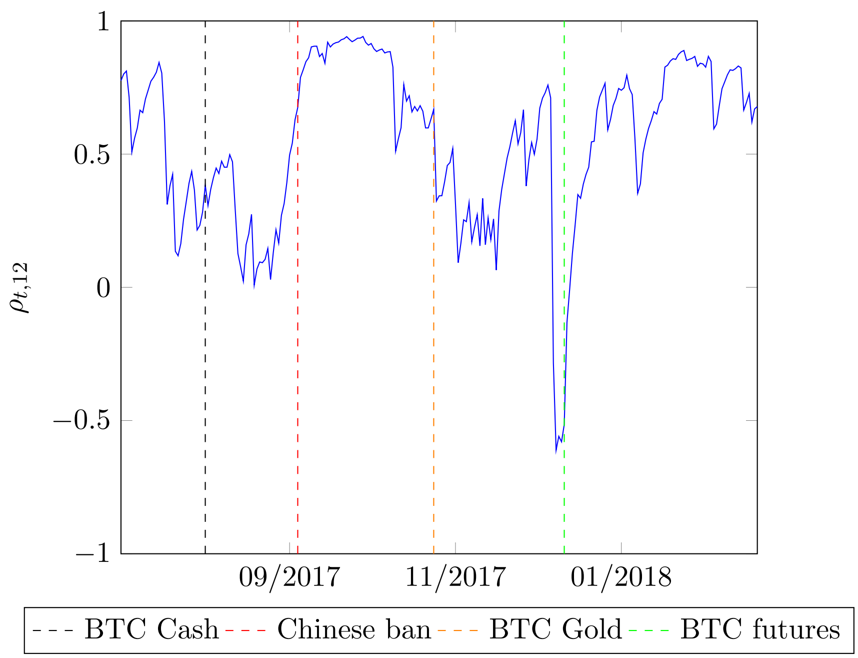
Table 6: Regression on time varying correlation

Independent	Panel A: SP500 vs. Coin					Panel B: NIKK vs. Coin					Panel C: BTC vs. Coin			
	BTC	DASH	LTC	XMR	XRP	BTC	DASH	LTC	XMR	XRP	DASH	LTC	XMR	XRP
Constant	-0.0656***	-0.1187***	-0.2410***	-0.3338***	-0.1836***	-0.0264	0.2236***	-0.0961***	-0.1780***	-0.1415***	0.0489***	0.8153***	0.1117***	0.1621***
	(0.0219)	(0.0242)	(0.0203)	(0.0193)	(0.0203)	(0.0250)	(0.0251)	(0.0220)	(0.0250)	(0.0204)	(0.0186)	(0.0161)	(0.0173)	(0.0174)
$r_{t,1}$	0.0662	-0.1713	-0.3584	-0.2351	-0.4766	-0.1471	-0.7514	0.2510	-0.2981	0.1002	-0.2589	0.2890**	0.2031	0.2109
	(0.8087)	(0.8799)	(0.6755)	(0.4975)	(0.7327)	(0.5263)	(0.4980)	(0.4374)	(0.3672)	(0.4886)	(0.1866)	(0.1410)	(0.1384)	(0.1730)
$r_{t,2}$	0.0406	0.0959	0.0690	0.0282	-0.0035	0.0572	0.1724**	0.0960	0.0601	-0.0533	0.0715	-0.2978***	-0.0833	-0.1878**
	(0.1426)	(0.0859)	(0.0740)	(0.0426)	(0.0717)	(0.1458)	(0.0788)	(0.0771)	(0.0503)	(0.0726)	(0.1058)	(0.0904)	(0.0702)	(0.0918)
$\sigma_{t,11}$	3.8084*	22.2250***	23.5850***	19.9940***	29.3680***	-7.0744***	-14.2480***	0.1766	-2.8033***	1.6557	7.5107***	-0.9377*	9.9110***	3.4994***
	(2.2345)	(2.4326)	(1.9207)	(1.2999)	(1.9738)	(1.5456)	(1.4958)	(1.1943)	(0.9464)	(1.3302)	(0.4864)	(0.4979)	(0.3304)	(0.4428)
$\sigma_{t,22}$	0.9295**	0.4414**	0.9626***	2.4536***	-0.2890*	2.4111***	0.2926*	0.9696***	2.5647***	1.5609***	0.2678	-1.9519***	-1.0230***	-0.9695***
	(0.3959)	(0.1709)	(0.1938)	(0.1810)	(0.1591)	(0.3724)	(0.1609)	(0.1922)	(0.2192)	(0.1209)	(0.2375)	(0.1548)	(0.2204)	(0.1551)
Dummies														
BTC futures	0.0178	-0.0141	-0.0012	-0.0321	-0.0808*	-0.0326	0.1775***	0.0520	0.1596***	-0.1001**	0.5032***	0.4060***	0.2015***	0.2563***
	(0.0464)	(0.0491)	(0.0385)	(0.0277)	(0.0446)	(0.0492)	(0.0452)	(0.0471)	(0.0333)	(0.0464)	(0.0476)	(0.0330)	(0.0348)	(0.0476)
Chinese ICO ban	0.0027	0.0913	0.0910**	0.0003	0.1074**	0.2743***	0.0660	0.1508***	0.0147	0.0045	0.0778	0.5794***	0.2599***	0.3136***
	(0.0518)	(0.0564)	(0.0440)	(0.0320)	(0.0470)	(0.0556)	(0.0528)	(0.0471)	(0.0390)	(0.0517)	(0.0549)	(0.0330)	(0.0403)	(0.0534)
BTC Cash	0.0202	0.0047	-0.0043	0.0942***	0.1279***	-0.2038***	0.0108	-0.0269	-0.0005	0.1315***	-0.0226	-0.3747***	-0.2590***	-0.1236***
	(0.0417)	(0.0440)	(0.0340)	(0.0251)	(0.0368)	(0.0454)	(0.0419)	(0.0367)	(0.0309)	(0.0409)	(0.0432)	(0.0294)	(0.0316)	(0.0421)
BTC Gold	-0.0238	-0.0392	-0.0097	-0.0181	-0.0883**	-0.0936*	-0.1689***	-0.1259***	-0.1241***	-0.1067**	-0.5315***	-0.5227***	-0.3139***	-0.3356***
	(0.0476)	(0.0515)	(0.0402)	(0.0293)	(0.0429)	(0.0506)	(0.0477)	(0.0426)	(0.0353)	(0.0468)	(0.0500)	(0.0345)	(0.0365)	(0.0485)
R^2	0.0175	0.0954	0.1850	0.3350	0.2280	0.0909	0.1350	0.0714	0.1780	0.1860	0.3010	0.3260	0.4720	0.1290
R^2 adjusted	0.0091	0.0877	0.1780	0.3290	0.2230	0.0828	0.1280	0.0631	0.1710	0.1780	0.2960	0.3220	0.4690	0.1240
Observations	937	937	937	937	937	912	912	912	912	912	1,361	1,361	1,361	1,361

Notes: This table provides the results from the OLS regression as outlined in equation (20). Panel A shows all models where the dependent variable is equal to correlation $\rho_{t,12}$ between SP500 and the cryptocurrencies. Panel B shows all models where the dependent variable is equal to correlation $\rho_{t,12}$ between NIKK and the cryptocurrencies. Panel C shows all models where the dependent variable is equal to the correlation $\rho_{t,12}$ between BTC and the other coins. Ordering of assets is set in accordance to the sequence just mentioned. Numbers between the parentheses denote the standard errors of the concerning coefficients. The asterisks ***, **, and * denote the statistical significance on a 1%, 5%, and 10% level, respectively. Programming of dummies is done according: $d = 0$ before, and $d = 1$ after the particular event. This concerns the following dates: BTC Cash (August 1, 2017); Chinese ICO ban (September 4, 2017); BTC Gold (October 24, 2017); and BTC futures (December 11, 2017).

seem to have had an economical large, positive, and highly significant impact, while the two hard forks exhibit a strong, negative, and significant relation with correlation. To examine the validity of these results, Figure 3 plots the time varying correlation between BTC and LTC along with the explicit identification of the selected events, as reflected by the dotted lines. Both the introduction of BTC futures and BTC Gold mark a clear turning point. Especially the introduction of the futures is worth discussing, as it caused a considerably jump in correlation between BTC and LTC. A possible explanation could be that investor confidence got a boost because BTC entered, as first ever cryptocurrency, the regulated market. The validity of the other two events is less evident. After the introduction of BTC Cash the correlation indeed decreased, but the effect was less pronounced than expected, and the correlation already exhibited an upward trend before the exact date of the Chinese ICO ban. However, in the period prior to the official Chinese statement, there was already heavily speculated on the future ban (Suberg, 2017). Therefore, it seems plausible to ascribe this preliminary increase to this particular event.

Figure 3: Time varying correlation: BTC and LTC



Notes: This figure illustrates the time varying correlation $\rho_{t,12}$ of BTC and LTC between July 2017 and February 2018. The dotted lines represent the dates of the event dummy variables listed in Table 6: black highlights the introduction of BTC Cash (August 1, 2017); red the Chinese ICO ban (September 4, 2017); orange the introduction of BTC Gold (October 24, 2017); and green the introduction of a BTC futures market (December 11, 2017).

6.4. Conclusion: time varying correlation

This section investigated the drivers of the time varying correlation between cryptocurrencies and the equity market, and between BTC and its peers. It can be concluded that the average time varying correlation between cryptocurrencies and the equity market is around zero, making cryptocurrencies an ideal portfolio candidate. The average correlation between BTC and the other coins is considerably higher but still well below $\rho_{t,12} = 1$ (i.e., perfect correlation). However, the actual correlation fluctuates heavily which requires frequent adjusted portfolio weights based on time varying correlation modeling. The main driver of time varying correlation in the models combining stock indices with cryptocurrencies turned out to be volatility. Both the volatility of SP500 and of the cryptocurrencies have a positive impact on their correlation, which is perfectly in line with the reasoning outlined in subsection 6.1. The volatility of NIKK, on the other hand, has a negative effect on correlation, while the impact of cryptocurrencies remained positive. This observation is somewhat surprising and could be the result of the reversed volatility spillover effect, as discussed in section 4. Between BTC and the other coins, the correlation remains highly affected by volatility. However, there are also a number of events that have had a major impact on the time varying correlation. The introduction of BTC futures and the Chinese ICO ban have contributed positively, whereas the hard forks exhibited a negative impact on correlation.

7. Return predictability

This section investigates the fourth and last phenomenon: *return predictability.* Subsection 7.1 provides the relevant background literature and economical reasoning behind the concept. Subsection 7.2 introduces the used framework to examine the return interaction of cryptocurrencies in a bivariate setting with stock indices. Finally, the empirical results are discussed in subsection 7.3, followed by the partial conclusion on return predictability in subsection 7.4.

7.1. Seeking return predictability

Return predictability of stock returns has received an enormous amount of attention within the academic literature over the last couple decades. Since the very existence of such ability is not only of interest to investors, but has also important implications for financial models of risk and return (Lettau and Van Nieuwerburgh, 2007). Kendall and Hill (1953) were the first who tested whether price changes could be predicted using past returns, while others expanded this analysis by including various predictive variables, such as market-to-book ratio, dividend yield, and the earnings-price ratio (Fama and French, 1988; Campbell and Shiller, 1988; Kothari and Shanken, 1997; Lewellen, 2004). More recently, McLean and Pontiff (2016) researched whether the found cross-sectional relations between these predictive variables and returns are robust in terms of return predictability, as the publications raised public awareness of these features. They find that, despite investors apparent ability to learn about mispricing, the return predictability of the various variables remains substantial even in the period post-publication.

The general reasoning for return predictability is that returns contain a time varying component, which enables forecasting of future returns. Due to its persistence, this component becomes even stronger over longer horizons (Fama and French, 1988). This finding was long questioned, since various papers found no clear advantage of longer horizon regressions in terms of predictive power, as outlined in Boudoukh et al. (2006). However, in recent years there has developed a general consensus that the predictability of returns is indeed strongest over long multiple-period horizons (Cochrane, 2007; Bollerslev et al., 2009). Although return predictability in the equity market seems to be directly derived from underlying economic fundamentals, this reasoning does not hold for cryptocurrencies. By examining the return predictability in a bivariate setting, combining stock indices with cryptocurrencies, and BTC with the other coins, it becomes possible to gain more insight in the actual market dynamics and fund flows, on both short and long horizons.

7.2. Methodology: VAR

To capture the return interaction between assets, this thesis uses a multivariate vector autoregressive (VAR) model. The general multivariate VAR(1) model is defined by (Tsay, 2010):

$$r_t = \phi_0 + \Phi r_{t-1} + \alpha_t \tag{21}$$

where r_t denotes the k-dimensional vector of log returns, ϕ_0 is a k-dimensional vector of constants, Φ is a $(k \times k)$ matrix of parameters, and α_t is a sequence of serially uncorrelated random vector with mean zero and covariance matrix Σ. In a bivariate setting ($k = 2$) it follows that:

$$r_{t,1} = \phi_{1,0} + \Phi_{1,1} r_{t-1,1} + \Phi_{1,2} r_{t-1,2} + \alpha_{t,1} \tag{22}$$

$$r_{t,2} = \phi_{2,0} + \Phi_{2,1} r_{t-1,1} + \Phi_{2,2} r_{t-1,2} + \alpha_{t,2} \tag{23}$$

where $\Phi_{1,1}$ and $\Phi_{2,2}$ denote the direct impact of past returns, while $\Phi_{1,2}$ and $\Phi_{2,1}$ denote the cross impact of past returns on current log returns. Subsequently, the distinct parameters are estimated equation-by-equation with linear regression.

To examine the return predictability over longer horizons, first the returns are being aggregated on a monthly basis according:

$$r_{m,i} = \sum_{t=0}^{20} r_{t,i} \tag{24}$$

where $r_{m,i}$ denotes the log return over month m of the i^{th} asset, and the returns $r_{t,i}$ are summed on a 20-day basis. Equation (24) is then implemented in equations (22) and (23), after which new parameters are estimated following the same procedure.

Subsequently, to assess whether the return predictability improves over time, a "VAR predictive regression" is performed, following Bollerslev et al. (2009). This method considers longer multi-period return regressions scaled by horizon h:

$$h = [1 : 12] \tag{25}$$

$$r_{m+1|m+h} = \sum_{s=1}^{h} r_{m+s} \tag{26}$$

where the monthly returns r_m are scaled over an h-month horizon. Subsequently, equation (26) is implemented in equations (22) and (23) which are then estimated equation-by-equation for each h-scaled period. To account for the partial overlap in returns, an OLS regression with Newey-West standard errors is executed (Newey and West, 1987).

Lastly, to assess the robustness of the VAR predictive regression results, an out-of-sample regression of predicted h-monthly scaled returns on realized returns is performed. This entails estimating the parameters of equations (22) and (23) using a limited number of observations, which are subsequently used in forecasting the remaining period (i.e., out-of-sample). The regression is defined by:

$$r_{h,i,r} = c + \gamma_1 r_{h,i,f} \tag{27}$$

where $r_{h,i,r}$ denotes the h-month realized log return of the i^{th} asset, c is a constant, γ_1 represents the concerning coefficient, and $r_{h,i,f}$ refers to the predicted return.

7.3. Empirical results

7.3.1. Baseline

Table 7 provides the parameter estimations for fourteen distinct VAR(1) models which consist of the same asset combinations as those used in section 4. From Panel A can be inferred that parameter $\Phi_{1,1}$ is economical small, negative, and insignificant for all models, implying that the impact of past log returns of SP500 on its current returns is marginal. Parameter $\Phi_{2,1}$ is economical larger with smaller standard errors and negative for all models, except for BTC. In the opposite direction, parameter $\Phi_{1,2}$ exhibits economical small and positive values for all models, except for XRP. Hence, the impact of SP500's past returns on the current returns of cryptocurrencies seems feasible, but not vice versa. Parameter $\Phi_{2,2}$ exhibits somewhat more mixed results, with positive values for BTC, LTC, and XRP, while negative for the remaining coins. However, a marginal positive impact of past log returns on the current returns of cryptocurrencies seems most feasible, given the significance levels.

From Panel B can be inferred that parameter $\Phi_{1,1}$ is considerably greater, negative, and with smaller standard errors for all models. This implies that the marginal impact of past log returns on NIKK's current returns seems more feasible. Parameter $\Phi_{2,2}$ exhibits a very comparable relationship to the one in Panel A. The same applies to the cross effect from NIKK to the cryptocurrencies, represented by parameter $\Phi_{2,1}$. In the opposite direction, parameter $\Phi_{1,2}$ shows slightly different results, with considerably larger and highly significant values for both BTC and LTC. Hence, the impact of NIKK's past returns on the current returns of cryptocurrencies seems feasible, while in opposite direction only BTC and LTC seem to marginally affect the returns of NIKK.

From Panel C can be inferred that parameter $\Phi_{1,1}$ is economical small, positive, and insignificant for all models, confirming the previous finding of a marginal positive impact of BTC's past log returns on its current returns. This impact seems less feasible for the other coins, reflected by the economical small an insignificant parameter $\Phi_{2,2}$ for all models. Parameters $\Phi_{2,1}$ and $\Phi_{1,2}$, represe-

Table 7: Parameter estimations VAR bivariate

	Panel A: SP500 vs. Coin					Panel B: NIKK vs. Coin					Panel C: BTC vs. Coin			
Parameter	BTC	DASH	LTC	XMR	XRP	BTC	DASH	LTC	XMR	XRP	DASH	LTC	XMR	XRP
$\phi_{1,0}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
$\phi_{2,0}$	0.0000	-0.0001	0.0000	0.0000	-0.0001	0.0000	-0.0001	0.0000	0.0000	-0.0001	0.0000	0.0000	0.0000	0.0000
	(0.0015)	(0.0027)	(0.0024)	(0.0030)	(0.0026)	(0.0016)	(0.0027)	(0.0024)	(0.0032)	(0.0029)	(0.0018)	(0.0016)	(0.0021)	(0.0020)
$\Phi_{1,1}$	-0.0118	-0.0113	-0.0092	-0.0106	-0.0101	-0.0461	-0.0506	-0.0481	-0.0494	-0.0491	0.0307	0.0434	0.0196	0.0294
	(0.0554)	(0.0553)	(0.0552)	(0.0552)	(0.0552)	(0.0543)	(0.0544)	(0.0546)	(0.0544)	(0.0545)	(0.0528)	(0.0580)	(0.0513)	(0.0516)
$\Phi_{2,1}$	0.0028	-0.1274	-0.1358	-0.1084	-0.2405	-0.0178	-0.0237	0.2223	-0.0529	-0.3238	-0.0815	0.0965	0.0211	-0.0691
	(0.1978)	(0.3485)	(0.2473)	(0.3980)	(0.2957)	(0.1035)	(0.1727)	(0.1402)	(0.2364)	(0.1682)	(0.0660)	(0.0776)	(0.0741)	(0.0756)
$\Phi_{1,2}$	0.0085	0.0028	0.0012	0.0023	-0.0020	0.0284***	0.0118**	0.0037	0.0039	0.0028	-0.0131	-0.0252	0.0030	-0.0181
	(0.0056)	(0.0029)	(0.0032)	(0.0025)	(0.0029)	(0.0095)	(0.0052)	(0.0050)	(0.0044)	(0.0042)	(0.0227)	(0.0281)	(0.0149)	(0.0213)
$\Phi_{2,2}$	0.0308	-0.0811	0.0733	-0.0216	0.1500**	0.0131	-0.0790	0.0650	-0.0133	0.1287	-0.0205	-0.0018	-0.0010	0.0237
	(0.0559)	(0.1077)	(0.0628)	(0.0424)	(0.0750)	(0.0574)	(0.1065)	(0.0645)	(0.0427)	(0.0822)	(0.0708)	(0.0612)	(0.0447)	(0.1078)
R^2 (index)	0.0024	0.0009	0.0002	0.0008	0.0005	0.0156	0.0106	0.0054	0.0058	0.0053	0.0009	0.0016	0.0005	0.0016
R^2 (coin)	0.0020	0.0088	0.0056	0.0006	0.0231	0.0012	0.0082	0.0057	0.0002	0.0189	0.0033	0.0037	0.0001	0.0015
Observations	937	937	937	937	937	912	912	912	912	912	1,361	1,361	1,361	1,361

Notes: This table presents the parameter estimations for fourteen distinct bivariate VAR(1) models as defined by equation (21). Panel A shows all bivariate models combining SP500 with the cryptocurrencies. Panel B shows all bivariate models combining NIKK with the cryptocurrencies. Panel C shows all bivariate models combining BTC with the other coins. Bivariate ordering is done according to the sequence just mentioned. Numbers between the parentheses denote the standard errors of the concerning parameters. The asterisks ***, **, and * denote the statistical significance on a 1%, 5%, and 10% level, respectively. "Index" refers to the asset fist named in the panel headers.

nting the cross impact between BTC and its peers, show mixed results. The impact of BTC's past log returns on the current returns of the other coins is negative for DASH and XRP, while positive for LTC and XMR. The impact in opposite direction is smaller and negative for all models, except for XMR. Hence, the cross impact seems feasible in both directions, but the sign is less evident.

Conducting a multivariate VAR(1), which incorporates all cryptocurrencies, could provide more insight in the nature of this relationship. Table 8 provides the parameter estimations for such model. On basis of the significant parameters, highlighted by the asterisks, it seems most feasible that the past log returns of cryptocurrencies have a negative impact on the current returns of their peers, which again could be an indication for return chasing behavior.

Table 8: Parameter estimations VAR multivariate (coins)

	BTC	DASH	LTC	XMR	XRP
Constant	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0011)	(0.0018)	(0.0016)	(0.0021)	(0.0020)
BTC	0.0472	-0.0110	-0.0209	0.0082	-0.0158
	(0.0602)	(0.0221)	(0.0273)	(0.0143)	(0.0210)
DASH	-0.1279*	-0.0303	0.0624	0.0370	-0.0718**
	(0.0752)	(0.0723)	(0.0460)	(0.0342)	(0.0332)
LTC	0.0640	0.0184	-0.0129	0.0301	0.0131
	(0.0816)	(0.0354)	(0.0613)	(0.0205)	(0.0273)
XMR	0.0203	0.0833**	-0.0291	-0.0068	-0.0623**
	(0.0776)	(0.0399)	(0.0374)	(0.0465)	(0.0303)
XRP	-0.2295**	0.0499	0.1251	0.0360	0.0033
	(0.0961)	(0.0485)	(0.0811)	(0.0333)	(0.1056)
R^2	0.0028	0.0111	0.0058	0.0079	0.0141
Observations	1,361	1,361	1,361	1,361	1,361

Notes: This table provides the parameter estimations for a multivariate VAR(1) model, as defined by equation (21), combining all cryptocurrencies. Numbers between the parentheses denote the standard errors of the concerning parameters. The asterisks ***, **, and * denote the statistical significance on a 1%, 5%, and 10% level, respectively.

7.3.2. Monthly aggregated

As discussed in subsection 7.1, return predictability tends to improve over longer horizons. To examine this property of cryptocurrency returns in a bivariate setting, Table 9 provides the parameter estimations of fourteen VAR(1) models with monthly aggregated returns. Furthermore, a VAR predictive regression is performed by scaling the returns over multiple months, which is illustrated for one model in Figure 4, followed by a robustness check visualized in Figure 5.

Table 9: Parameter estimations VAR bivariate (monthly aggregated)

	Panel A: SP500 vs. Coin					Panel B: NIKK vs. Coin					Panel C: BTC vs. Coin			
Parameter	BTC	DASH	LTC	XMR	XRP	BTC	DASH	LTC	XMR	XRP	DASH	LTC	XMR	XRP
$\phi_{1,0}$	-0.0004	-0.0001	-0.0003	-0.0002	-0.0002	-0.0005	-0.0002	-0.0004	-0.0004	-0.0005	0.0016	0.0017	0.0016	0.0017
	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0075)	(0.0073)	(0.0074)	(0.0074)	(0.0074)	(0.0200)	(0.0200)	(0.0199)	(0.0200)
$\phi_{2,0}$	0.0033	0.0076	0.0053	-0.0024	0.0082	0.0014	0.0061	0.0047	-0.0020	0.0025	0.0046	0.0030	-0.0128	0.0014
	(0.0309)	(0.0578)	(0.0561)	(0.0659)	(0.0740)	(0.0303)	(0.0569)	(0.0522)	(0.0695)	(0.0760)	(0.0334)	(0.0340)	(0.0437)	(0.0540)
$\Phi_{1,1}$	-0.0350	0.0302	-0.0141	0.0083	0.0194	0.0196	0.0389	0.0200	0.0177	0.0214	0.1292	0.1255	0.1835	0.1653
	(0.1448)	(0.1366)	(0.1362)	(0.1403)	(0.1404)	(0.1585)	(0.1489)	(0.1616)	(0.1623)	(0.1600)	(0.1216)	(0.1309)	(0.1233)	(0.1237)
$\Phi_{2,1}$	0.8543	0.9224	0.8137	0.5185	4.3461	0.1165	-0.5275	-0.2723	0.9985	1.7650	0.3744	0.3148	0.6385**	0.5337
	(0.9355)	(1.5207)	(1.6216)	(2.4512)	(2.7854)	(0.4461)	(0.9845)	(0.6513)	(1.3569)	(1.6304)	(0.2347)	(0.3451)	(0.3025)	(0.4332)
$\Phi_{1,2}$	0.0204	-0.0063	0.0103	0.0061	0.0058	0.0004	-0.0259	-0.0030	-0.0065	0.0045	0.0289	0.0281	-0.0339	-0.0141
	(0.0190)	(0.0112)	(0.0093)	(0.0078)	(0.0064)	(0.0423)	(0.0172)	(0.0161)	(0.0135)	(0.0103)	(0.0660)	(0.0694)	(0.0388)	(0.0597)
$\Phi_{2,2}$	0.0282	0.0755	0.1019	0.0645	0.2509	0.1420	0.1220	0.0743	-0.0573	0.1566	0.1996	0.0504	-0.1438	-0.0206
	(0.1598)	(0.1632)	(0.1938)	(0.1372)	(0.2067)	(0.1863)	(0.1519)	(0.2084)	(0.1551)	(0.2046)	(0.1752)	(0.1456)	(0.1159)	(0.0854)
R^2 (index)	0.0252	0.0106	0.0232	0.0128	0.0151	0.0046	0.0438	0.0050	0.0083	0.0068	0.0311	0.0306	0.0344	0.0303
R^2 (coin)	0.0209	0.0287	0.0241	0.0069	0.1047	0.0271	0.0352	0.0174	0.0162	0.0518	0.1372	0.0521	0.1444	0.0369
Observations	46	46	46	46	46	45	45	45	45	45	68	68	68	68

Notes: This table presents the parameter estimations for fourteen distinct monthly aggregated bivariate VAR(1) models as defined by equation (21). Panel A shows all bivariate models combining SP500 with the cryptocurrencies. Panel B shows all bivariate models combining NIKK with the cryptocurrencies. Panel C shows all bivariate models combining BTC with the other coins. Bivariate ordering is done according to the sequence just mentioned. Numbers between the parentheses denote the standard errors of the concerning parameters. The asterisks ***, **, and * denote the statistical significance on a 1%, 5%, and 10% level, respectively. Monthly returns are aggregated on a 20-day basis, as defined by equation (24). "Index" refers to the asset fist named in the panel headers.

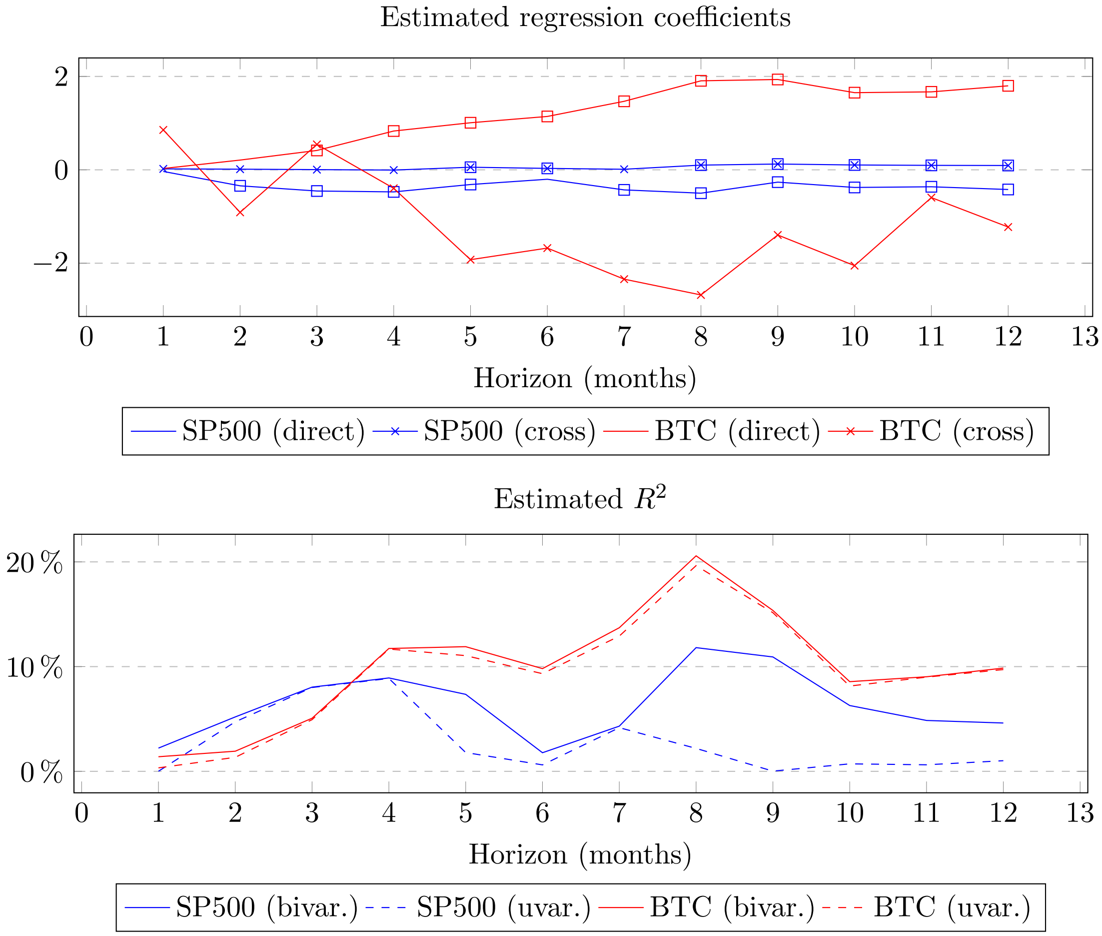
From Table 9 can be inferred that the explanatory power R^2 increased for nearly all assets in the various models, by aggregating the daily log returns on a monthly basis. However, the statistical significance hardly improved for most parameters. The parameters $\Phi_{1,1}$ and $\Phi_{2,2}$ in Panel A are economical of equal size, but more often positive. The cross impact, however, substantially increased as parameters $\Phi_{2,1}$ and $\Phi_{1,2}$ exhibit economical larger and more positive values, with smaller standard errors in general. Especially the impact of SP500's past month log returns seem to have a strong positive impact on current month returns of cryptocurrencies, while the impact in opposite direction remains unfeasible.

Panel B provides a somewhat different picture. Parameter $\Phi_{1,1}$ is of equal size, as compared to Table 7, but changed sign, while $\Phi_{2,2}$ exhibits also more positive and economical slightly larger values. The one-way cross impact seems to have increased again, as parameter $\Phi_{2,1}$ is economical larger and more often positive, while parameter $\Phi_{1,2}$ decreased both in size and significance. Hence, NIKK's past month log returns seem to have a strong positive effect on current month returns of cryptocurrencies, except for DASH and LTC, while the impact in opposite direction seems unfeasible.

For all bivariate models combining BTC with the other coins, both the one-way direct and cross impact seem to have increased, as presented in Panel C. Parameter $\Phi_{1,1}$ is economical large, with relatively small standard errors, which indicates a positive impact of BTC's past month log returns on its current month returns. In addition, parameter $\Phi_{2,1}$ exhibits economical large and relatively significant values, indicating a strong positive impact of BTC's past month returns on current month current returns of its peers. While parameters $\Phi_{1,2}$ and $\Phi_{2,2}$ also exhibit economical larger values, their sign is less evident and, moreover, the large standard errors make them unreliable.

To assess whether predictability improves even further by scaling the log returns over multiple months, the VAR predictive regression results for the bivariate model combining SP500 and BTC are visualized in Figure 4. The upper plot illustrates the estimated regression coefficients, while the lower plot shows the development of R^2 over the scaled h-months period. From this figure can be inferred that the direct impact of SP500's past month returns marginally increases over a three month horizon, after which the negative coefficient remains rather stable. Whereas the direct impact of BTC's past month returns on its scaled returns is positive and increases substantially until eight months, after which the coefficient slightly decreases. The cross impact of SP500's past month returns on the h-month returns of cryptocurrencies increases significantly by scaling and reaches its peak at eight months. The impact in opposite direction is only marginal up to seven months, after which the impact increases gradually, reaching its peak at a nine month horizon. Hence, it seems likely that positive log returns of SP500 have a negative effect on the monthly aggregated returns of cryptocurrencies, whereas the returns of BTC seem to have a marginal but positive effect on the monthly scaled returns of SP500, especially on a eight to nine month basis. This is also supported by the observed R^2 jump of SP500 in the bivariate model as compared to its univariate compeer, as illustrated in Figure 4. The estimated R^2 of BTC remained considerably higher over almost the entire horizon, but its improvement compared to the univariate model is

Figure 4: VAR predictive regression: SP500 and BTC

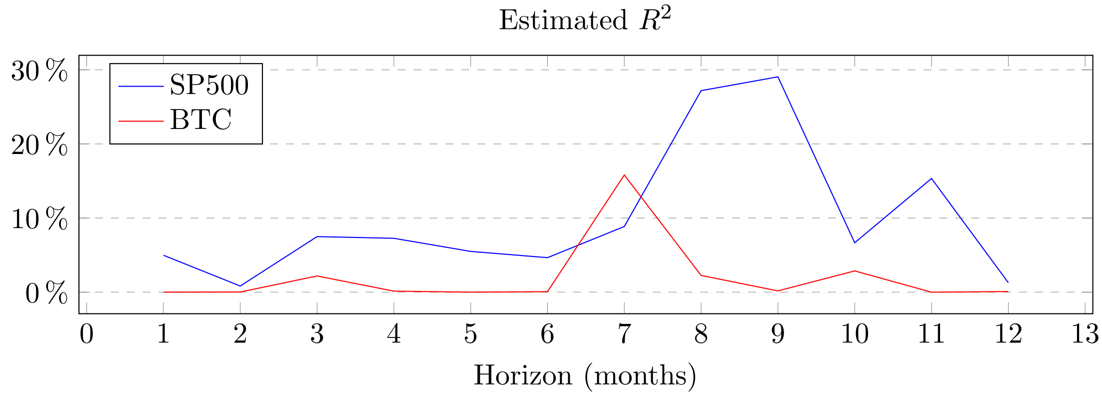


Notes: This figure illustrates the estimated slope coefficients along with the corresponding R^2s from the regression of the scaled h-period SP500 and BTC returns on their respectively monthly returns, as defined by equations (22) to (26). All of the regressions are based on 20-day aggregated observations from June 2014 to February 2018. The direct regression coefficients represent the long term predictive ability of monthly returns within the same asset, while the cross coefficients reflect this ability between the different assets. For example, SP500 (cross) entails the impact of BTC's monthly returns on SP500's scaled returns. Coefficients which are significant on a 10% level are marked with squares. Univariate models are denoted by "uvar.", while bivariate models are denoted by "bivar.".

only marginal. Nevertheless, it can be concluded that the estimated R^2 of return predictability for both SP500 and BTC increased substantially by scaling the returns over multiple months.

To examine the robustness of this observation, the estimated R^2 for both assets in an out-of-sample regression of the predicted h-scaled monthly returns on realized returns is presented in Figure 5. From this figure can be inferred that the out-of-sample return predictability of SP500 remained intact for most horizons, and is indeed best performing on an eight to nine month basis. This in contrast to the return predictability of BTC, which turned out to be only robust on a seven month horizon.

Figure 5: Out-of-sample robustness: SP500 and BTC



Notes: This figure illustrates the estimated R^2 from the out-of-sample regression of predicted h-scaled monthly returns on realized returns for both SP500 and BTC, as defined by equation (27). All of the regressions are based on 20-day aggregated observations from June 2014 to February 2018. The sample consists of 20 monthly returns (in-sample), leaving 26 observations for the out-of-sample forecast, as can be inferred from Table 9.

7.4. Conclusion: return predictability

This section investigated the return predictability in a bivariate setting combining cryptocurrencies with the equity market, and between cryptocurrencies mutually in both a bivariate and multivariate setting. In addition, the return predictability over longer horizons was examined. It can be concluded that the impact of SP500's past returns on current returns is only marginal negative, while this impact seems somewhat more feasible for NIKK. The direct impact of cryptocurrencies' past returns on their current returns is somewhat greater but the actual sign is less evident. The cross impact turned out to be one-way traffic for all models. The past returns of SP500, NIKK, and BTC have a negative impact on the current returns of (other) cryptocurrencies, while the impact in opposite direction is negligible. This is a strong indication for return chasing behavior both in the direction from cryptocurrencies to the equity market and in the direction from the other coins to BTC. Apparently, cryptocurrency investors shift to the more regular assets after these securities experienced positive returns, perhaps due to the difference in volatility and thus risk. Aggregating the returns on a monthly basis did not alter the direction of the impact but changed the sign of the effect, however, indicating a positive return spillover effect from the equity market to the cryptocurrency market. One possible explanation is that profits from the more regular equity market are transferred to the cryptocurrency market. However, when examining the aggregated monthly returns over longer horizons, this effect proved not to be robust (i.e., coefficient switched sign), while it provided even more evidence for the return chasing argument. Furthermore, the h-scaled return predictability of SP500 seems to improve by including the returns of BTC and reaches its peak at an eight to nine month horizon. The return predictability of BTC improved only marginal by including SP500 and is merely robust on a seven month basis.

8. Conclusion

With the recent introduction of various financial derivatives related to cryptocurrencies, the digital coins are gradually establishing a position within the regulated markets. It seems to be a matter of time before securities like BTC, DASH, LTC, XMR, and XRP are regarded as mature financial products. However, little is known about the dynamics between the more conventional and the cryptocurrency market yet. This thesis contributes to the academic literature by examining the market dynamics between these five cryptocurrencies and two stock indices, which enables to draw generalizing conclusions. Similar studies, which consider such broad range of coins, have not been performed yet, resulting in a number of new remarkable insights.

To expose potential market dynamics, this study examined four distinct phenomena, which presence is well known from the equity market, each discussed in a separate section. Section 4 documented the emergence and appearance of volatility spillovers between the different assets, by introducing a multivariate BEKK-GARCH model. Section 5 covered the traditional asymmetric leverage effect and its potential appearance in the dataset, by using a univariate GJR-GARCH model. Section 6 built on the framework introduced in section 4 and used the dynamic model to expose the time varying correlation between the distinct assets and its most important drivers. Lastly, section 7 introduced a multivariate VAR model to assess return interaction and predictability over both short and long horizons.

This study has led to the subsequent findings. Firstly, the empirical results provide convincing evidence for the presence of one-way volatility spillovers in the direction from the equity market and BTC to the (other) cryptocurrencies. This implies that both SP500 and NIKK serve as important indicators for market risk on the cryptocurrency market, despite their lack of rational economic interrelationship, presumably fueled by speculative trading. The observed impact of BTC on the volatility of its peers seems more rational, as it possibly can be explained by BTC's dominant position, making it the most important benchmark for most cryptocurrency investors. Secondly, in line with previous research, the results provide no evidence for the presence of a traditional asymmetric leverage effect in the data of cryptocurrencies. As the coins lack economic fundamentals, the rational leveraging mechanism does not function, analogically. However, the results do provide evidence for a reversed effect, possibly indicating more irrational behavior such as risk seeking or return chasing in the cryptocurrency market. Thirdly, this study stresses the importance of modeling time varying correlation for portfolio management involving stock indices and cryptocurrencies, since the actual correlation between the distinct assets fluctuates heavily, which requires frequent adjusted portfolio weights. The main driver of the time varying correlation between the equity market and cryptocurrencies proved to be volatility, whereas the correlation between BTC and its peers is predominately determined by regulatory shocks and hard forks. Lastly, the cross impact of one asset's past returns on another asset's current returns turned out to be one-way traffic for all models, highlighting a negative impact from the equity market and BTC on the returns of the (other) cryptocurrencies. This is a strong indication for return chasing behavior, both in in the direction from cryptocurrencies to the equity market as well as in the direction from the other coins to BTC. Aggregating the returns on a monthly basis did not alter the direction of impact but changed the sign of the effect. However, by scaling the monthly returns over longer horizons, this sign switch proved not to be robust, while it provided even more evidence for the return chasing argument. Furthermore, the return predictability of SP500 substantially improved both by including the returns of BTC as well as by scaling the monthly returns over multiple months, which proved to be robust out-of-sample. The return predictability of BTC improved only marginal by including the returns of SP500 and performed considerably worse in the out-of-sample robustness assessment.

These new insights provide a sound base for further research concerning cryptocurrencies. Whereas this thesis only considers the dynamics between the equity market and cryptocurrencies, further research should be done to explore the dynamics with other more conventional assets, such as bonds or various exchange rates. In addition, the inclusion of a stock index composed of technology stocks, like the NASDAQ-100, could provide even more prove of interaction with the cryptocurrency market. With respect to the documented volatility interaction, it is interesting to expand the analysis from a bivariate to a multivariate model, combining multiple coins and stock indices. As the used BEKK-GARCH model can only handle a limited number of assets at once, this is a small limitation to this research. Furthermore, the observation of a reversed asymmetric leverage effect provides food for thought. From a behavioral perspective, it is worth the effort to investigate whether this effect proves to be robust over time and is indeed caused by risk seeking or return chasing behavior, as suggested by this study. The findings regarding the drivers of the time varying correlation could be implemented in an extensive investment portfolio analysis, by using the found relations in estimating future correlations with the aim of maximizing the sharpe ratio. In addition, it is interesting to further research the impact of forks on the correlation within the cryptocurrency market. Since this thesis provides no decisive answer on whether this impact is robust over time, due to a perceived disruptive change to the blockchain, or is just of temporary nature. Another interesting angle lies in a further research on the mutual return predictability between the equity market and cryptocurrencies, in order to examine the highlighted robustness on a larger and more emphasized scale. Concluding, a last limitation to this study concerns the limited number of observations in the dataset used, especially in the sections examining the monthly aggregated returns. However, as most cryptocurrencies were only recently introduced to the market, this proved to be an insurmountable shortcoming. Therefore, it is interesting to expand on this study, by examining a larger range of coins over a longer period, in the coming years. If only because these digital coins probably play an even bigger role in our financial system by then.

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